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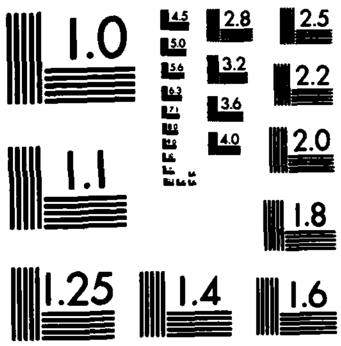

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Forecasting Enlistment Supply

A Time Series of Cross Sections Model

Robert F. Cotterman

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Because the military relies on voluntary enlistments to fill its entry-level positions, there has been widespread interest in estimating how military enlistments respond to various supply factors, both those originating in the civilian sector (e.g. business cycles) and those over which the military exerts some control (e.g. recruiters). To help the military anticipate manpower shortages before they develop, these estimated supply parameters are used to predict the future course of enlistments under various hypothetical situations. This report documents research on a model of the supply of high-aptitude, high school diploma graduate, nonprior service male enlistees. Its emphasis is on methodology, including variable construction and methods of estimation and forecasting. It applies the methodology to monthly state-level data over the period October 1974 through March 1981, and produces fitted equations for the four services that relate the enlistment rate to military/civilian pay, the number of recruiters per potential enlistee, a business cycle variable, and other control variables reflecting changes in enlistment policy, including the end of the GI Bill. It then uses the fitted models in conjunction with future scenarios to obtain forecasts of "high quality," nonprior service male enlistments.

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Forecasting Enlistment Supply

A Time Series of Cross Sections Model

Robert F. Cotterman

July 1986

Prepared for the
Office of the Assistant Secretary of Defense/
Force Management and Personnel

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PREFACE

This report documents research on ways of forecasting the number of high-quality enlistments into the active duty armed forces. Such forecasts play an essential role in assessing the future viability of the personnel force, in determining whether future enlistments will satisfy congressionally imposed quality constraints, and in allocating recruiting resources among the military Services. The author discusses the development of a new methodology for quantifying the determinants of past enlistment behavior and for forecasting future enlistments. The methodology has been used at The Rand Corporation to provide forecasts to the Office of the Assistant Secretary of Defense for Force Management and Personnel, which supported the research. The study was made in Rand's Defense Manpower Research Center under the auspices of the Federally Funded Research and Development Center sponsored by the Office of the Secretary of Defense.

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SUMMARY

Because the military relies on voluntary enlistments to fill its entry-level positions, there has been widespread interest in estimating how military enlistments respond to various supply factors, both those originating in the civilian sector (e.g., business cycles) and those over which the military exerts some control (e.g., recruiters). To help the military anticipate manpower shortages before they actually develop, these estimated supply parameters are used to predict the future course of enlistments under various hypothetical situations.

This report documents research on a model of the supply of high-aptitude, high school diploma graduate, non-prior service male enlistees. The emphasis is on methodology, including variable construction and methods of estimation and forecasting. The methodology is applied to monthly state-level data over the period October 1974 through March 1981. The output is fitted equations for the four Services that relate the enlistment rate to military/civilian pay, the number of recruiters per potential enlistee, a business cycle variable, and other control variables reflecting changes in enlistment policy, including the end of the GI Bill. The fitted models are then used in conjunction with future scenarios to obtain forecasts of "high quality" (AFQT category I-IIIA, high school graduate), non-prior service male enlistments.

METHODOLOGY

To researchers and policymakers concerned with enlistment forecasting, the two-stage process of estimation and forecasting probably seems quite familiar. However, the methodology developed here departs from past practice in a number of significant ways:

- Enlistment relationships for the four Services are treated as a system of equations to increase the efficiency of estimation.
- Through the covariance structure of the disturbances, the system allows for factors that are unobserved in the available data but which nevertheless affect enlistments for the various Services and states simultaneously. In treating observations as independent, past analyses of enlistment rates have generally ignored these factors. The covariance structure allows correlations in disturbances from one period to the next, allows nationwide components that are correlated across Services and

that affect Services' enlistment rates in all states at a point in time, and allows state-specific components that are correlated across Services within each state at a given time.

- The methodology conveniently permits the researcher to examine the effect of changing the covariance structure on the coefficient estimates of the observed variables. In particular, the covariance structure can be restricted to mimic the kind of structure typifying past studies. A key finding of experimentation with these restrictions is that the coefficient estimates are sensitive: wage and business cycle effects are often higher under the restricted covariance structure, for example. Further, the reported standard errors obtained when treating observations as independent are frequently much lower than when interdependencies are recognized; ignoring the interdependencies leads one to place more faith in the estimates than is in fact warranted.
- The methodology provides a fully integrated approach to forecasting. The forecasts embody information from the scenarios as well as from the serial correlation of disturbances. Allowing for serial correlation, which is estimated here to be moderate, especially improves the accuracy of near-term forecasts. The methodology also correctly computes the standard errors of the forecasts, which has not generally been done in previous studies.
- The methodology is specified for use with data on a time series of cross sections. In fact, the model is applied to monthly rates of high-quality enlistments (for each Service) by state. The advantages of such data over either national time series or single cross sections are discussed in the text.

EMPIRICAL RESULTS

In the research discussed in this report, the model was applied to data from October 1974 to March 1981. Because further development of the model is planned (see below), the results of the present application of the model should be considered illustrative of the methodology. The chief results may be summarized as follows:

For each Service, the equations fit the data very well, as is reflected in the close correspondence between the actual and predicted numbers of high-quality enlistments over the years 1974–81. The predictions are usually within several hundred of the actual number of such enlistments.

As expected, *the enlistment rate increases as military/civilian pay increases and recruiters increase, and decreases as economic conditions improve.* The pay effect appears to be smaller than commonly thought, a result at least partly attributable to the more realistic covariance structure. The effect of economic conditions is larger than in previous work. This finding may stem in part from a more accurate construction of the business cycle variable. In particular, economic conditions are measured by the deviation in employment from trend, a procedure which is arguably superior to using simply an unemployment rate (see Sec. II). The effect of employment conditions becomes even stronger under a restricted (less appropriate) covariance structure. Recruiter effects are positive and, like pay and economic conditions, statistically significant. However, further refinement of this variable, and the way it is specified in the model, seems desirable. Thus, present estimates of recruiter effects should be received cautiously.

The effect of ending the Vietnam-era GI Bill is negative, with the reduction in high-quality enlistments the greatest for the Army.

Estimates of the covariance structure reveal a moderate month-to-month correlation in the disturbances for each Service. That is, in any state a Service with high recent enlistment rates can expect fairly high rates over the near future, after controlling for pay, recruiters, and economic conditions. *Results also show a high positive cross-Service correlation in the nationwide components at a point in time.* If the Army is doing well nationwide, for instance, the other Services are also likely to be doing well nationwide. One might expect such a pattern as a result of national advertising campaigns, or because Services' changes in their management of recruiting are *de facto* coordinated nationally with one another, or because changes in the recruiting climate tend to affect all Services nationally rather than only a single Service. The national components also lead to small-to-moderate cross-state correlations in a Service's disturbances at a point in time. If a Service is doing unusually well in one state, it is fairly likely to be doing well in other states, too, after controlling for observable factors. Finally, *within-state* correlations of the state-specific disturbances across Services are quite small. Other things equal, state-specific unobserved factors leading the Navy to do well do not generalize to the other Services. In sum, the chief factors in the covariance structure appear to be a moderate serial correlation for each Service, a high correlation across Services in their national components at any point in time, and small-to-moderate cross-state correlations in the disturbances for a particular Service at a given time.

FORECASTS

Parameter estimates from the model are used to forecast enlistments for FY82 though FY90 under four alternative cyclical scenarios. Two of the scenarios consider extreme business cycle conditions: either a continuous recession or a continuous expansion. A third scenario assumes that the economy stays on an even keel. The fourth and most realistic scenario assumes that the economy will gradually improve over time in the manner predicted by the unemployment rate forecasts of Data Resources, Incorporated. All forecasts assume that recruiter levels and the ratio of military to civilian pay will remain at their FY82 levels, that the new GI Bill was not introduced, and that the population of young males will decline as predicted by Census figures.

Forecasts for the final half of FY81 that are based on actual values of the explanatory variables are somewhat lower than observed enlistments in each Service, but the extent of underprediction is generally modest. Predictions for FY82 that are based on actual or estimated values of the explanatory variables are lower than preliminary counts of actual FY82 enlistments for the Navy and Marine Corps and much lower for the Army. Although it is hard to imagine a set of plausible parameter estimates for the included supply factors that would explain the extraordinary success of the Army in FY82, there may be omitted variables that would account for some of the discrepancy. In particular, the Army's ultra-VEAP kicker program (providing educational benefits) may have had an effect on FY82 enlistments, but the model does not permit a role for these kickers. Experimental evidence suggests, however, that this program could not have had a major effect on FY82 enlistments.

These underprediction problems notwithstanding, it seems unlikely that the Services will achieve the FY82 enlistment levels again over the next eight years in the absence of a worsening of the aggregate economy. The shrinking population of young males will cause some decline in enlistment levels even if the economy continues to be sluggish. In addition, the economy is expected to improve, which should cause substantial declines in enlistments over time for all the Services.

FUTURE WORK

The development of the methodology is not complete. Although the current version of the model incorporates a rich covariance structure among the disturbances, that structure does not allow for differences in the variance of the disturbances from state to state (heteroskedasticity). Enlistment rates of large states, however, might be expected to

have lower error variances than those of small states, and the model could be generalized to permit this possibility.

In addition, further work will be required to isolate the source of the Army's remarkable recruiting success in FY82.

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CONTENTS

TABLES

I. INTRODUCTION

Since the advent of the personnel force, the military meets its manpower needs through the retention of military personnel and through the voluntary enlistment of civilians. Because non-prior service (NPS) males form the bulk of enlistments, there has been well-deserved interest in models designed to forecast future enlistments of NPS males. Provided that these models predict well, they may be used to forecast manpower shortages so that appropriate policy changes may be made to forestall their occurrence.

One major type of forecasting model, exemplified by the work of Fernandez (1979), relies on time series of national aggregate data to obtain parameter estimates, which are in turn used to predict future enlistments. An unfortunate feature of time-series data for the 1970s is that there is little independent movement in many variables of interest, and as a consequence individual parameters are frequently measured with little precision. Imprecise estimates for individual parameters do not necessarily pose problems for forecasting as long as the future scenario is one for which the explanatory variables are assumed to move together in the same way as they did in the 1970s. If, as is frequently the case, one wishes to entertain scenarios in which the explanatory variables do not move as they have in the past, then imprecision in individual parameter estimates generally implies imprecision in forecasts.

A second approach to predicting enlistments has been to use cross-sectional data to estimate supply parameters. Although cross-sectional data typically offer much more independent variation in key variables, thereby avoiding the collinearity problem plaguing time-series data, there remain unanswered questions concerning the appropriateness of using parameters that have been estimated cross sectionally to forecast over time. Cross-sectional variation in a variable may have a different meaning than time-series variation in the same variable because the two types of variation result from different underlying causes. If so, parameter estimates derived from cross-sectional data may not be useful in evaluating what will happen in the future as variables change over time.

Yet a third approach, followed, for example, by Goldberg (1982), uses a time series of cross sections to obtain the parameter estimates used in forecasting enlistments. The cross-sectional content of these data again removes the collinearity problem in using purely time-series

data. Moreover, because there are multiple observations on each cross-sectional unit of observation, it is not necessary to rely solely on cross-sectional variation. Indeed, it is possible through the use of area indicator variables to prevent parameter estimates from being influenced by certain kinds of cross-sectional variation. The latter opportunities have not often been exploited in practice, however.

The current study is of the latter variety in that it uses data from a time series of cross sections, but this study differs in a number of ways from most previous work in this field. First, although the menu of supply factors examined here is common to most other studies, some variables—position in the business cycle in particular—are measured differently. Second, this study takes at least limited advantage of the aforementioned opportunities to remove cross-sectional variation that seems especially troublesome. Third, this work attempts to improve efficiency in estimation by taking advantage of covariances in the disturbances of the enlistment supply equations. These disturbances are permitted to covary over time, over the cross-sectional units of observation, and across Services. These distinguishing features are discussed more fully when the basic model, including variable definitions and the covariance structure, is presented in Sec. II.

Because of the more general covariance structure allowed here, generalized least squares techniques are used in estimation and forecasting. The estimation procedures, as well as the estimates themselves, are examined in Sec. III. The estimation results indicate that permitting a more general covariance structure does affect estimates and reported standard errors, but estimated supply responses are generally not dramatically different from those found elsewhere.

Section IV gives the forecasting methodology, the actual forecasts, and—in something of a break with past tradition in this field—the correctly computed standard errors for the forecasts. Enlistments are expected to fall substantially over the remainder of the 1980s because of both anticipated improvements in the aggregate economy and declines in the population of young males.

Finally, Sec. V sums up what has been learned from these efforts, and the three appendices provide technical details.

II. THE SPECIFICATION OF THE MODEL

This section describes the structure of the basic enlistment supply model and the data used to estimate the model. The data are state-level monthly observations for October 1974 through March 1981. After discussing the choice of variables in the first subsection, the second subsection presents the covariance structure.

Attention is restricted here to enlistments of NPS males who are high school diploma graduates (HSDG) in Armed Forces Qualification Test (AFQT) categories I-IIIA (50th percentile and above).[1] The reason for the restriction to so-called "high-quality" NPS males is twofold. First, the Services are especially interested in attracting high-quality males. Second, the estimation procedure requires that enlistments be supply-constrained, and the latter assumption may not be tenable over the whole estimation period for females and for lower-quality males.

CHOICE OF VARIABLES

The enlistment supply model used here is of the form

$$y_{bst} = \sum_j x_{bstj}\beta_{bj} + u_{bst} \tag{1}$$

where y_{bst} is the enlistment rate for Service b in state s at time t, x_{bstj} is the value of the jth explanatory variable for Service b in state s at time t, β_{bj} is a Service-specific parameter that gives the partial effect of the jth explanatory variable on the Service-specific enlistment rate, and u_{bst} is a stochastic disturbance term. Notice that the parameters β_{bj} are assumed to be invariant over time and across states but are permitted to vary across Services. Since the data used to estimate Eq. (1) are monthly time series for states in the United States, t is measured in months.

Considering first the dependent variable, the enlistment rate y_{bst} is defined to be the number of enlistment contracts signed for Service b at time t in state s, divided by the population of 17-21 year old males

[1]Estimation results and forecasts for HSDG males in AFQT category IIIB are given in App. C. As noted there, I have substantial misgivings about the appropriateness of estimating such a model for the latter group because I suspect that enlistments of this group have sometimes been demand-constrained in the past.

at time t in state s.[2] The contract counts for each Service are restricted to high-quality NPS males who enter active duty at some time after signing a contract.[3] The AFQT category groupings use the renorming algorithm in effect as of March 1982, the time at which these data were supplied by the Defense Manpower Data Center (DMDC).[4] The male youth population figures were obtained on a year-by-state basis from a National Cancer Institute study and were linearly interpolated to form monthly estimates. Although it is true that older males do in fact enlist and are included in the enlistment counts, the bulk of enlistments are drawn from the 17-21 year old group, and this group thus serves as a useful benchmark population.[5]

The list of variables x_{bstj} used to explain the enlistment rate includes measures of position in the business cycle, the ratio of military pay to civilian pay, recruiter intensity, educational benefits offered by the Services, and miscellaneous dummy variables. These variables, which are defined briefly in Table 1, are discussed in detail below.

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[2]Note that the enlistment rate is entered linearly rather than logarithmically. To my knowledge, no one has provided statistical evidence on whether the linear or the logarithmic form is preferable in this particular application, although it would in principle be possible to conduct the appropriate tests using the Box-Cox methodology. Lacking such evidence, I have chosen the linear form because its use substantially simplifies the computation of forecast standard errors.

[3]Although missing values for AFQT category or educational attaintment did not appear to be a problem in general, missing values were very unevenly distributed over time. To prevent what might otherwise appear (incorrectly) to be low enlistment levels, I imputed AFQT categories and educational levels where they were missing. The basis for this imputation was to assume that missing values occurred randomly and to assign new values based on the individual's service, race, reported educational level, and reported AFQT category. This assignment algorithm used national level data for the time interval during which the missing value occurred. Three such time intervals were used: calendar years 1973-75, 1976-77, and 1978 onwards.

[4]Although the enlistment data were obtained in March 1982, the estimation period stops with March 1981 because individuals may delay their entry into active duty for up to one year after signing an enlistment contract.

[5]Because the numerator of the enlistment rate y_{bst} counts only high-quality males, logical consistency suggests that the population figure in the denominator be similarly restricted to high-quality males. Predictions of future enlistments, however, would then require predictions of the population size of high-quality males, which could perhaps be obtained by investigating demographic trends. Such investigations were considered to be beyond the scope of the current work but are worth pursuing in the future. The assumption underlying the current model is that high-quality males have been and will continue to be a constant fraction of the male population.

Table 1

EXPLANATORY VARIABLES IN THE ENLISTMENT STUDY MODEL[a]

CYCLE	Proportionate deviation of total state employment from its trend
LWPAY	Natural logarithm of the ratio of average weekly Regular Military Compensation to average weekly earnings of manufacturing production workers in the state
LREC	Natural logarithm of the ratio of a Service's national recruiting force to the national population of 17-21 year old males
GIBILL	Indicator variable having the value one through December 1976, zero afterwards
Miscellaneous indicator variables:	
	Month-of-year indicators
	State indicators
	Indicator variables for November 1976, December 1976, January 1977, February 1977, calendar year 1977
	Indicator variable for the period up to and including February 1976

[a]See text for more detailed variable definitions.

Position in the Business Cycle (CYCLE)

Variables serving as proxies for the level of aggregate demand or position in the business cycle attempt to measure the ease with which jobs may be obtained in the civilian sector. In periods of low aggregate demand, jobs of a given quality are expected to be harder to obtain, particularly for the young, than in periods of high aggregate demand. Consequently, other things equal, the enlistment rate is expected to move countercyclically.

The variable used here (CYCLE) measures position in the business cycle as (roughly) the percentage deviation of total employment[6] from its trend, divided by 100. More precisely, the values of CYCLE for a particular state are the residuals from a regression of the natural logarithm of employment in that state on time, time squared, and monthly indicator variables.[7] Because $\ln(1 + x)$ is approximately equal to x for small values of x, CYCLE multiplied by 100 has the interpretation of

[6]More specifically, total employment is restricted to civilian nonagricultural employment.

[7]Data for the regressions typically covered the period January 1952 to October 1981.

(approximately) the percentage deviation of employment from trend.[8] The employment data come from the Bureau of Labor Statistics (BLS).

This cyclical measure is thought to be superior to the unemployment rate because the latter, although available monthly at the state level, suffers from two important problems. First, as has been noted by Smith and Welch (1978), there appear to be quasi-permanent cross-state differences in levels of unemployment rates. Because business cycles do not exhibit such permanence, it seems unlikely that cross-state differences in unemployment rates pick up purely cyclical fluctuations.[9] Second, individual states vary in the methods they use to estimate the unemployment rates reported by the BLS. Although monthly figures are renormed so that they mesh with a yearly average computed independently from the Current Population Surveys (CPS), the month-to-month movements in series from different states still may not be meaningfully compared. These problems do not appear to plague the alternative cyclical measure used here, however. By virtue of the method used to compute deviations from trend, the deviations for one state cannot all be of the same sign (at least over the interval 1952 through 1981), and I see no compelling reason for lack of comparability across states.

Relative Pay (LWPAY)

Because enlistments are assumed to respond positively to pecuniary rewards in the military and negatively to pecuniary rewards in the civilian sector, virtually all supply models include measures of military and civilian pay. The variable used here, LWPAY, is defined as the natural logarithm of the ratio of average weekly Regular Military Compensation (RMC) to the average weekly earnings of production workers in manufacturing. The weekly RMC is computed as one-fourth the annual RMC of an E-1 plus three-fourths the annual RMC of an E-2, divided by 52. The data on average weekly earnings of production workers in manufacturing are from monthly BLS establishment series for each state.

The weighted average of RMCs used in constructing LWPAY attempts to measure military pay during the enlistee's first year of service. Using a weighted average of RMCs drawn from a wider range of

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[8] That is, CYCLE = ℓn (employment/trend employment) = ℓn (1 + (deviation from trend employment/trend employment)) = $\simeq$ (deviation from trend employment/trend employment).

[9] Truly permanent cross-state differences could be handled through the inclusion of state-specific indicator variables.

the lower enlisted grades would not give substantially different results: military pay is entered logarithmically, and pay rates in the lower enlisted grades tended to move proportionately over the period of observation.

The choice of a civilian wage measure is based on a number of considerations. First, this wage series is one of the very few that is both based on reasonably large samples and available monthly for each state over the period of estimation. Hence, this series requires no fabrication. Second, given that a single statistic is being used to capture what is in fact a whole distribution of alternative civilian wages of potential enlistees, this particular statistic does not seem unreasonable. Although the civilian wage of a particular potential enlistee may, because of differences in age and experience, be lower than the average wage of production workers in manufacturing, the proportional relationship between the wages may be approximately the same over time.

One of the more compelling alternative measures of civilian earnings that could be used is a wage series for young males only. Although I completely agree that what matters is the alternative civilian earnings of young males (in this case presumably HSDG males in AFQT categories I-IIIA), the crucial question is whether a better estimate of the true pay effect will be obtained by using *measured* youth wages. If earnings of manufacturing production workers are proportional to *correctly measured* youth wages,[10] the true pay effect will be obtained using the manufacturing wage series despite the fact that the latter series is not based solely on youth. Violation of this proportionality assumption is unlikely to be sufficiently important (over the estimation period) to offset the other substantial advantages that the manufacturing wage series offers over a youth wage series.[11]

A youth wage series, although superficially appealing, suffers from a number of problems, particularly in the context of a model using monthly observations at the state level. Perhaps the most important of these problems is measurement error. There is, to my knowledge, only one source of youth wage data by state for even a moderate number of points in time during the estimation period: the CPS. Even the CPS, however, gathers wage data in only two months of the year, March and May, and the March data base is retrospective (earnings

[10]Proportionality is all that is required because civilian pay enters the supply equation logarithmically. Because state dummies are included in the regression (see below), the factors of proportionality are even permitted to differ across states.

[11]Tan and Ward (1984) provide some evidence along these lines. They show that the ratio of earnings of new labor market entrants to peak wage earners changed little within education classes over the interval 1974-80. (See Tables 2 and 3 of Tan and Ward, 1984.)

last year) rather than contemporaneous. Youth wages in other months would have to be imputed. In addition, the number of enlistment-age male high school graduates with usable wage data in a CPS is likely to be fairly small, perhaps on the order of 3000 nationwide. One would therefore obtain sample sizes on the order of 60 per state on average (far fewer in many states), which are far smaller sample sizes than those used to compute average hourly earnings of production workers in manufacturing.[12] Hence, even if a youth wage series were a more desirable alternative on other grounds, one might use average hourly earnings of production workers in manufacturing because the latter data require no fabrication to obtain temporal detail and because they are likely to contain much less sampling error.

Although the measurement error problem would itself lead me to reject the use of a youth wage series, two other potential difficulties should not go unmentioned: an endogeneity problem and a sample selection problem. These problems are most easily examined in isolation from one another.

An endogeneity problem could occur because the military employs a nontrivial fraction of male youth, and it would therefore not be surprising to find that civilian wages of male youth depend partly on current and past enlistment levels. If so, then the relationship between contemporaneous enlistments and youth wages will reflect not simply the depressing effect of higher civilian wages on military enlistments. The relationship will also reflect the positive influence of current enlistments on the current wages of youth.[13] In addition, if there is positive serial correlation in the disturbances of Eq. (1), a positive relationship between current enlistments and current youth wages can arise out of positive covariance between each of these variables and past levels of enlistments. These endogeneity arguments suggest that using current wages of youth as an exogenous variable in explaining enlistments is

[12]Sample sizes used to compute average hourly earnings of production workers in manufacturing are on the order of 10 million nationwide.

[13]This argument, as well as the sample selection arguments in the next paragraph, ignores the direct role of military enlistments in determining the composition of the civilian youth labor market. The military draws disproportionate numbers of high-quality males who would be expected to have higher civilian wage rates than their low-quality contemporaries. Larger enlistments of high-quality young males would, on this account alone, reduce the measured average wage for young civilian males, for the latter group would then be more heavily weighted with low-quality, low-wage males. This compositional argument by itself therefore implies a spurious negative relationship between high-quality enlistments and measured average youth wages, which would result in an overstated pay effect.

likely to result in an understatement of the true depressing effect of civilian income opportunities on enlistments.[14]

The sample selection problem could bias the estimated pay effect in either direction. The difficulty here is that the average wage is necessarily computed over only those male youths who work. At any time during the school year, the fraction of young males who work is substantially less than one, and many of those who do work are at part-time jobs for which the wage rate may or may not accurately portray the opportunity cost relevant for the enlistment decision. Moreover, this pattern of job holding reflects individual choices of whether and how much to work. For this reason, samples of young male workers are likely to be selected nonrandomly from the population of all young males, and the mean wage computed over these workers may be quite different from the mean computed over the whole population of young males.[15] The proportion of young males who work varies both over time and in cross section. Thus, the cross-sectional or time-series differences in the observed mean wages of young men reflect both differences in the means of the *population* wage distributions and differences in the intensity of sampling along the wage distributions. Differences of the former variety may be useful indicators of differences in average alternative wages (aside from the endogeneity problem discussed above). Differences of the latter kind, however, arise from endogenous individual decisions and are not directly useful in measuring differences in average alternative wages in the male youth population as a whole.

The endogeneity and sample selection problems should not be important for the manufacturing wage series used here because the population of manufacturing workers contains a broad spectrum of age groups. There may, however, be another difficulty in using this or virtually any other wage series: cross-sectional wage variation may be of a different nature than the time-series variation desired for forecasting purposes. For example, it seems likely that the extent of unionization has independent effects on both the wage rate and the enlistment rate. Unionism rates vary across states but have varied little over time, at least at the national level, during the period under consideration. Because unionism rates are not controlled for in this model, cross-sectional wage variation would be expected to pick up a unionization effect that is absent in time series. To the extent that effects such as

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[14]This problem may also be viewed from a forecasting perspective. It would make little sense to predict future enlistments conditional on future wage rates of youth if future wage rates are themselves dependent on the future enlistments that are to be predicted.

[15]The latter point is one of the simple but important lessons from the recent labor economics literature on selection bias (see, for example, Heckman, 1979).

these are constant over time for a given state, however, they may be removed by permitting each state to have a unique intercept in the enlistment Eq. (1). For this and similar reasons, state dummies are included in the list of explanatory variables. I note in passing that the opportunity to include state dummies is one advantage in using a time series of cross sections that is clearly unavailable when using a single cross section.

Recruiter Intensity (LREC)

Recruiter intensity for each Service is measured as the natural logarithm of the ratio of that Service's recruiters at the national level to the national population of 17-21 year old males. Recruiter intensity is expected to have a positive influence on the enlistment rate. It is assumed, however, that the enlistment rate for each Service is unaffected by other Services' recruiters.[16]

The variable LREC for each Service varies only over time, not in cross section. That is, at a given point in time the same recruiter intensity is assumed for each state. I have not attempted a state-level breakdown of recruiters for two reasons. First, measurement error at the state level seems likely to be very important. State-by-state recruiter breakdowns exist at only a few points in time, and given that even the national aggregate figures gathered by different researchers frequently disagree strongly, it is hard to put much faith in the state-level breakdowns that do exist. Second, even if meaningful cross-sectional data were available, it may not be possible to use cross-sectional variation in recruiters and enlistments to obtain a structural recruiter effect directly. If Services attempt to maximize the flow of high-quality recruits, they would allocate disproportionately large numbers of recruiters to the most fertile recruiting areas. Hence, the cross-sectional relationship between recruiters and enlistments will reflect, in part, this allocation rule, leading to an upward bias in the estimated effect on enlistments of adding one more recruiter.[17]

The latter problem could arise in an aggregate time-series context as well if the Services choose to have especially high levels of recruiters when they (correctly) anticipate a particularly strong recruiting

[16]Although cross-Service recruiter effects are a real possibility, it was felt that the recruiter data were too crude to produce believable cross-Service estimates.

[17]This reasoning assumes that recruiter impact is not determined simply by population size. Actually, if LREC enters Eq. (1) linearly, as assumed in this model, recruiters should be allocated across states in direct proportion to the state population of young males; i.e., recruiter intensity should be identical across states. I would not want to push this point, however.

climate. Three factors make this possibility seem somewhat unlikely. First, the Services face substantial year-to-year budgetary uncertainty. Even if a Service planned to increase its recruiters in anticipation of a strong recruiting climate, its plans could change if faced with an unexpectedly small budget. Second, the usefulness of such intertemporal reallocations are limited by the unpredictability of the recruiting climate in the distant future. Finally, from the Services' perspective there is probably less substitutability over time than across areas of the country. That is, the Services are likely to be fairly indifferent to a choice between a recruit from Oregon and an otherwise similar recruit from New York, but they would probably not be indifferent between taking an additional recruit in 1979 and taking an additional recruit in 1983. This lack of intertemporal substitutability would limit the advantages of intertemporal reallocation of recruiters.

A more serious problem with the recruiting intensity measure used here is that it fails to consider possible changes over time in the effort expended by individual recruiters. Recent work by Dertouzos (1984) points to substantial effects of Army enlistment quotas on the productivity of Army recruiters.

Finally, it is worth noting a disturbing feature of recruiter data: estimated recruiter effects appear to depend heavily on the particular series chosen. For the estimates given in this report, I use series supplied by Lawrence Goldberg that are thought to contain consistent definitions over time.[18] Preliminary analysis using recruiter series that were spliced together from a variety of sources yielded estimated recruiter effects that were generally lower.

Educational Benefits and Other Inducements To Enlist (GIBILL)

Over the period under consideration, the Services offered a variety of post-Service educational benefits and other nonwage inducements to enlist. Perhaps the most notable of these is the Vietnam-era GI Bill, which was available to all enlistees signing contracts on or before December 31, 1976. To capture the effect of replacing the GI Bill with the Veterans' Educational Assistance Program (VEAP), its less generous successor, the model includes a dummy variable, GIBILL, having the value one through December of 1976 and the value zero afterwards. Although the potential benefits of the GI Bill varied over time in real

[18]The Goldberg data are annual observations for October 1975 onwards. For October 1974 through September 1975, I use quarterly recruiter data, supplied by Richard Fernandez of Rand, that have been normalized so that the means of the latter series match the means of the Goldberg series for October 1975 through September 1976.

terms because of inflation, nominal benefits were periodically revised to keep approximate pace with inflation. Hence, the implicit assumption that the expected value of the GI Bill to potential recruits remained fixed over time prior to 1977 is not unreasonable.[19]

In addition to the switch from the GI Bill to VEAP, there have at times been Service-conducted experiments with other enlistment incentives: monetary supplements to VEAP, reduced terms of enlistment, and enlistment bonuses. Discussion of these programs is conveniently split along Service lines.

For Services other than the Army, I attempted to estimate effects of a number of incentives that were part of the Multiple Option Recruiting Experiment (MORE) and the Educational Assistance Test Program (EATP). The programs examined were those that analyses of the experimental data by Haggstrom et al. (1981) and Fernandez (1982) found to have potentially important effects. When variables measuring the proportion of each state covered by each program were used in preliminary data analyses, however, no discernible effects were found. Some of these programs were in effect for only a few months over the period of observation or for very limited geographical areas, so the inability to find measurable impacts is perhaps not too surprising. Part of the difficulty is that these experimental programs did not use the state as the geographical unit of analysis. The state-level data set used here thus fails to take advantage of the balanced test design and blurs the distinction between experimental areas and control areas. It is probably not too important to estimate these program effects for forecasting purposes, however, because none of the future scenarios to be entertained includes the reintroduction of any of these programs. Hence, variables reflecting these experimental programs are excluded from the current model.

For the Army, experimentation with post-Service educational benefits, particularly the monetary supplements to VEAP ("kickers"), was more extensive than for the other Services, both in terms of proportion of the country covered and in terms of duration of the experiments. I initially attempted to estimate the effects of these educational benefits programs individually by using the proportion of each state's youth population that was eligible for a given program, but I was unable to estimate individual effects with any precision. Thinking that the problem lay in letting the data attempt to identify a parameter for each individual program, I then tried to constrain the relative effects of different programs in rough accordance with findings from the

[19]The transition period immediately before and somewhat after expiration of the GI Bill requires additional treatment, as is discussed below.

experimental data (Haggstrom et al., 1981; Fernandez 1982). Doing so yielded effects that were typically minisule and were still estimated with little precision. These variables were subsequently dropped and are not included in any of the results presented in this report.

Because the Army now uses a generous, nationwide, educational benefits program (providing lump-sum enhancements of $8000 to $12,000, depending on the term of enlistment) that may be partly responsible for the Army's recent recruiting success, future analysis of Army enlistments may be able to identify the program's effects. An alternative that could be explored in future work is to use a mixed estimation scheme to build in the parameter estimates that have been obtained from the experimental data.

Miscellaneous Indicator Variables

Numerous indicator (dummy) variables are used in this analysis to control for a variety of factors. The enlistment rate equation includes 11 monthly dummies for each Service in order to control for seasonality in enlistments that is not caused by the substantive explanatory variables. Each equation also includes state dummies because there may be permanent cross-state differences in enlistment rates associated with permanent unobserved factors, which could in turn be correlated with the remaining explanatory variables. The aforementioned cross-state variation in unionization rates is an illustration of the latter point.

Additional dummy variables are introduced to deal with the unusual enlistment patterns that arose as a consequence of the elimination of the GI Bill. Because the demise of the GI Bill was announced in advance of its expiration, and VEAP was less attractive than the GI Bill, knowledgeable recruits who would otherwise have enlisted after December 1976 had incentives to shift their contract date forward to 1976 to gain eligibility for the GI Bill. With complete knowledge on the part of all potential enlistees, one would expect to find unusually high enlistment rates at the end of 1976 and unusually low enlistment rates in early 1977, gradually rising to approach from below a new, lower (when compared with the GI Bill era), equilibrium enlistment rate. Potential enlistees may not, however, have had complete information. Some may not have realized that the GI Bill had expired, and others may have mistakenly believed that VEAP was as generous as the GI Bill. In the extreme case in which no potential enlistees were aware that the GI Bill was to expire and in which correct information was gained only gradually after the GI Bill had already expired, one would expect to find enlistment rates declining in early 1977 to approach from above a new, lower, equilibrium level.

The data in fact appear to indicate a combination of these two forces, i.e., foresight and knowledge on the part of some, although not all, potential enlistees. Enlistment rates appear to be unusually high in November and December of 1976 and unusually low in January and February of 1977. For perhaps a year or more afterwards, enlistment rates appear to be somewhat above their new long-run equilibrium level (except in the Marine Corps where they are slightly below). In an attempt to control for these effects, the enlistment rate equation for each Service is specified to include individual month dummies for November and December of 1976 and for January and February of 1977. In addition, a dummy variable for calendar year 1977 is included in each equation, thereby permitting the intercept to differ in that year. A question worth investigating in future work is whether these calendar year dummies are really picking up lagged responses to the switch from GI Bill to VEAP or are instead picking up some other effects.

Finally, dummy variables are included to allow for the possibility that AFQT categories are not completely comparable over time. Before 1976 the individual Services were giving their own tests to potential enlistees (see Office of the Assistant Secretary of Defense, 1980 and 1982), and the resulting AFQT scores may have differed from those that would have been obtained on the Armed Services Vocational Aptitude Battery (ASVAB) exams given in later years. The levels of high-quality enlistments do in fact appear to be unusually high during this initial period.[20] For this reason, the enlistment rate equation for each Service includes a "misnorming" dummy that assumes a value of one through February 1976 and a value of zero afterwards.[21] (This variable has a value of one even for the first two months of 1976 because exam dates need not coincide with contract dates, and many of those enlisting in early 1976 may have taken their exams in 1975.)

Not surprisingly, inclusion of a misnorming dummy has a substantial negative impact on the estimated effect of the GI Bill, and it is possible that the misnorming dummy is absorbing some effects that should be attributed to the GI Bill. Unfortunately, there seems to be no way to resolve this issue with these data. It might help to replace

[20]I found a similar phenomenon in earlier work with accessions data.

[21]Renormed enlistment counts are used for later years to account for the misnorming that is known to have occurred over that period. Briefly, misnorming may have occurred prior to 1976 (when renormed data are not available), and misnorming is known to have occurred in later years (when renormed data are available). It is worth noting that simply using renormed data may not solve all of the problems caused by the original misnorming. In particular, recruiters might have acted differently if they had known the true quality mix of the enlistees that were entering. I am indebted to James Hosek for this point.

no way to resolve this issue with these data. It might help to replace the GI Bill dummy with a variable measuring the expected present value of all post-Service educational benefits regardless of the source (GI Bill, VEAP, VEAP kickers), but, as has been explained by Fernandez (1981), this procedure is itself fraught with problems.

THE ERROR STRUCTURE

Attention now turns to the specification of the error structure, i.e., the relationships among the stochastic disturbances, u_{bst}. To guide the reader through this subsection, it may be useful to provide a brief preview.[22] The basic regression disturbance u_{bst} for a particular state (s), Service (b), and month (t) will first be specified to depend upon two factors: (1) the regression disturbance in the preceding month for the same state and Service and (2) new noise that is uncorrelated with past disturbances. This new noise for a particular state, Service, and month will then be written as the sum of two mutually uncorrelated terms, a national component common to all states and a state-specific component. Because the national component is common to all states, its presence implies that the new noise for a particular Service in one state is contemporaneously correlated with the new noise for that same Service in other states. Cross-Service correlations in the new noise arise from two sources. First, the national components are permitted to covary across Services, which implies that the new noise for a particular state and Service may be correlated with the new noise for *other* states and other Services. Second, correlation is also permitted between the state-specific components for different Services in the *same* state, which provides an additional source of cross-Service correlation *within* a given state.

Although the assumption that the disturbances are serially uncorrelated is convenient and is sometimes invoked, it seems unreasonable. It is common to find serial correlation in the disturbances of regression relationships involving economic time series, and previous studies of enlistment behavior have discovered significant positive serial correlation in the residuals of monthly models (see, for example, Fernandez, 1979). This study, therefore, assumes that the disturbances for a particular state and Service follow a covariance stationary, first-order autoregressive (AR(1)) process:

[22]Throughout this discussion, keep in mind that the state and month-of-year indicator variables imply that the corresponding effects are treated as fixed rather than random.

$$u_{bst} = \rho_b u_{bs\,t-1} + \varphi_{bst} \tag{2}$$

where $E(\varphi_{bst}) = 0$

$E(\varphi_{bst}\varphi_{bst'}) = 0, t \neq t'$

and $0 \leq |\rho_b| < 1$

Equation (2) states that the disturbance in any month (for a particular Service and state) is a fraction ρ_b of the disturbance in the preceding month, plus some new noise φ_{bst} that is uncorrelated with past disturbances. The fractions ρ_b are assumed to be identical across states but are permitted to vary across Services.

Next consider the covariance of disturbance terms across states at a point in time. In most cross-sectional enlistment supply models, it is assumed that disturbances for any particular Service are uncorrelated over the cross-sectional units of observation. This assumption seems likely to be inappropriate, however, because there are undoubtedly many unobserved factors affecting a Service's enlistments that are common to all states. To capture this idea, a components of variance scheme is assumed to apply to the φ_{bst}. Specifically, φ_{bst} is assumed to be decomposed into a national-level serially uncorrelated component, λ_{bt}, which affects the Service b enlistment rate in all states equally at time t, and a state-specific serially uncorrelated component, ϵ_{bst}, which is assumed to be uncorrelated with the ϵ_{bst} in other states and with the λ_{bt}:

$$\varphi_{bst} = \lambda_{bt} + \epsilon_{bst} \tag{3}$$

where $E(\lambda_{bt}) = E(\epsilon_{bst}) = 0$

$$E(\lambda_{bt}\lambda_{b't'}) = \begin{cases} \omega_{bb'} \text{ if } t = t' \\ 0 \text{ otherwise} \end{cases}$$

$$E(\epsilon_{bst}\epsilon_{b's't'}) = \begin{cases} \gamma_{bb'} \text{ if } t = t' \text{ and } s = s' \\ 0 \text{ otherwise} \end{cases}$$

$E(\lambda_{bt}\epsilon_{b'st'}) = 0$ for all b, s, t, b', t'

The λ_{bt} might capture, for example, changes in a Service's advertising in national media, changes in federally funded student loan programs, or nationwide changes in attitudes toward the military. The ϵ_{bst} might

pick up such factors as changes in tuition charges for state universities or unobserved changes in state-level civilian labor demand.

The above covariance structure also provides for cross-Service correlations. Because some factors entering the λ_{bt} may well affect all Services, the λ_{bt} are allowed to covary across Services. Similar reasoning suggests that the ϵ_{bst} are likely to covary across Services within a state, and hence the latter type of covariance is permitted as well.

Summarizing this discussion, serial correlation in the basic disturbances u_{bst} for any state and Service is assumed to occur via an AR(1) process. At any point in time, the φ_{bst} are correlated across states for a given Service because of the presence of a national-level component λ_{bt}, and are correlated across states for different Services because of cross-Service covariance in the λ_{bt}. Within a state at a point in time, the φ_{bst} are correlated across Services because of cross-Service correlations in both the national-level components λ_{bt} and the state-specific components ϵ_{bst}.[23]

Putting all of the above assumptions together, each of the basic regression disturbances, u_{bst}, is correlated with the basic regression disturbances in all other states, Services, and months:

$$E(u_{bst}u_{b's't'}) = \begin{cases} (\omega_{bb'} + \gamma_{bb'})\rho_b^{t-t'}/(1 - \rho_b\rho_{b'}), \text{ if } s = s' \\ \\ \omega_{bb'}\rho_b^{t-t'}/(1 - \rho_b\rho_{b'}), \text{ if } s \neq s' \end{cases} \tag{4}$$

where $t \geq t'$.[24] Notice, however, that all of these covariances may be described in terms of only 24 basic parameters: four values of ρ_b (one for each Service), 10 (nonredundant) values of $\omega_{bb'}$, and 10 (nonredundant) values of $\gamma_{bb'}$.[25]

[23]A possibility that is not addressed in this report is that the state-level disturbances are heteroskedastic because of cross-state differences in the size of the youth population.

[24]Equation (4) assumes that the AR(1) processes have been in operation for an infinitely long time.

[25]To see that there are 10 nonredundant values of $\omega_{bb'}$ (and of $\gamma_{bb'}$), imagine the $\omega_{bb'}$ (or the $\gamma_{bb'}$) to be arrayed in a 4 × 4 covariance matrix. Although such a matrix would contain 16 elements, symmetry implies that all elements on one side of the diagonal are redundant.

III. ESTIMATION METHODOLOGY AND RESULTS

With the covariance structure given in Sec. II, efficient estimation requires that the supply parameters β_{bj} for all Services be estimated jointly through a generalized least squares (GLS) procedure. Before discussing the GLS procedure used here, however, it may be useful to point out the consequences of estimating the parameters for each Service separately by ordinary least squares (OLS), as is frequently done, if in fact the disturbances are correlated in the manner described above. First, OLS parameter estimates are inefficient in the sense of having larger true standard errors than the GLS estimates.[1] Second, the reported OLS standard errors on parameter estimates and forecasts are invalid. Third, the OLS forecasts are inefficient both because the parameter estimates employed in forecasting are themselves inefficient and because the OLS forecasts make no use of the serial correlation in the error terms. That is, if the disturbances are serially correlated, then disturbances at one point in time are helpful in predicting future values for the disturbances and thus future enlistments. This information is used in GLS forecasts but is ignored in OLS forecasts.[2]

COMPUTATIONAL CONSIDERATIONS

To reduce computational problems in estimation and prediction, the input data were first modified to include complete time series for 15 states plus complete time series at the national aggregate level.[3] The reasons for this modification are most easily discussed by considering the modification to occur in two steps. The first step is a reduction to

[1]These efficiency comparisons are valid in small samples if the covariance matrix of the disturbances is known. When the covariance matrix must be estimated, as is the case here, the efficiency comparisons are valid asymptotically (i.e., in large samples). In addition, all of these efficiency comparisons ignore "second best" considerations. That is, in real-world data analysis one undoubtedly commits a host of econometric sins, and in such cases one can never be completely sure that improvements in one dimension will result in "better" estimates.

[2]The importance of this efficiency gain in GLS forecasts over OLS forecasts should vary directly with the size of ρ and with the size of the disturbance in the final observation period, and inversely with the distance of the forecast period from the final period of observation.

[3]The national aggregate data are formed by taking weighted averages of the state-level data. The weight assigned to a particular state is the fraction of the national population of male youth residing in that state.

15 individual states and an aggregate state, which is composed of the remaining 36 states (the District of Columbia is treated as a state). The second step is replacement of the data for the aggregate state with data at the national aggregate level.

The reason for taking the first of these steps is to circumvent the computational problem that would otherwise arise because of the large number of state dummy variables (one for each Service in each state). Although the coefficients on these state dummies are not required to produce aggregate forecasts, and it is therefore not necessary to compute coefficients for these dummies, it is necessary to manipulate large matrices to control for these state effects in estimation. Including each state individually would impose a substantial increase in computational cost and complexity. The sample of 15 individual states chosen for inclusion are the 15 largest in terms of total population[4] (1979 estimates): California, New York, Texas, Pennsylvania, Illinois, Ohio, Michigan, Florida, New Jersey, Massachusetts, North Carolina, Indiana, Virginia, Georgia, and Missouri.

The reason for taking the second step—replacing the aggregate state's observations with those at the national aggregate level—is to avoid computing the weighted sums across states required to produce national aggregate forecasts. When the national aggregates are used in place of data for the aggregate state, the national-level intercept is available directly, and forecasts may be produced from the national series alone. Taking this second step has *no effect* on the resulting estimates or forecasts. That is, as is demonstrated in App. B, GLS estimates and forecasts are unaffected by a nonsingular linear transformation of the data, provided that the appropriate covariance matrix of disturbances is used in GLS.[5]

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[4]The basis for choosing to enter the 15 largest states individually is an errors-in-the-variables argument. I suspect that measurement error in the explanatory variables is more serious for the smaller states and that this problem is partially remedied by the averaging process of aggregating the smaller states into a single composite. An alternative criterion for deciding which states to include individually would be to minimize the within-group variation of the explanatory variables in the 36-state aggregate. (Recall that the disturbances are assumed to be homoskedastic, and thus all states' regression relationships are assumed to be equally noisy.)

[5]Introducing the national aggregate data does change the covariance matrix of disturbances used in estimation relative to what it would be if only state-level observations were used (see App. B). That is, because the national aggregate data are weighted averages of the state-level data, the disturbances in the national aggregate equations exhibit different variances and covariances than do the disturbances in the state-level equations.

THE ESTIMATION METHOD

This subsection summarizes briefly the salient features of the GLS technique used to estimate the model; additional technical details may be found in App. B. Readers who are uninterested in the estimation methodology may skip this subsection without losing continuity.

The GLS estimation method that is applied to the sample of 15 states plus the national aggregate borrows heavily from Parks (1967), who developed an efficient method for estimating a model with a similar structure. The Parks model contains a system of unrestricted regression equations in which the disturbances in each equation follow an AR(1) process, and the new noise at each point in time is correlated across equations in an arbitrary fashion. The model in this report is of the same form except that here there are cross-equation restrictions on the β_{bj} and the ρ_b, and the covariance matrix of the φ_{bst} is assumed to have a special pattern. The Parks procedure has therefore been modified to deal with these additional restrictions.

Estimation is carried out in two basic stages. In the first stage, the covariance matrix of the disturbances is estimated; in the second stage, this estimate is used to calculate the GLS parameter estimates. Perhaps the simplest way to understand the idea behind this procedure is to note, first, that if the autocorrelation coefficients ρ_b were known, one could quasi-difference the data for each Service and state to yield[6]

$$y_{bst} - \rho_b y_{bs\,t-1} = \sum_j (x_{bstj} - \rho_b x_{bs\,t-1\,j})\beta_{bj} + \varphi_{bst} \tag{5}$$

It is clear from Eq. (5) that the time series of quasi-differenced data for a particular state and Service obeys a linear regression. Moreover, because the φ_{bst} are serially uncorrelated, these regressions may be viewed as a set of "seemingly unrelated regressions" with cross-equation constraints (the β_{bj} vary only across Services, not across states) and a special form for the contemporaneous covariance matrix of disturbances. One could then apply constrained joint GLS to estimate the parameters β_{bj}.

These ideas are used in estimation here except that the unknown true values of ρ_b are replaced by estimated values. Specifically, values of ρ_b are obtained in two steps. First, an OLS regression of the enlistment rate on the explanatory variables is run for each Service separately using data from the 15 individual states. The resulting regression residuals for each Service are then regressed on the first lagged value of

[6] As demonstrated in App. B, a relationship similar to Eq. (5) holds for the national aggregate data provided that the fractions of male youth residing in each state remain unchanged over time.

the residuals (again using the 15 individual states), and the coefficient estimates so obtained are the estimates of ρ_b.[7]

The estimated ρ_b are applied to quasi-difference the data (as in Eq. (5)) for each of the 15 individual states, and these quasi-differenced data are used in another round of OLS for each Service. Residuals from the latter regressions are employed to estimate the values of $\omega_{bb'}$ (the covariances of the national components) and $\gamma_{bb'}$ (the covariances of the state-specific components) as follows.[8] Letting e_{bst} denote the residual for Service b in state s at time t,[9] $\omega_{bb'}$ is estimated as the average value of $e_{bst}e_{b's't}$ computed over all pairs of non-identical states ($s \neq s'$) and all months. That is,

$$\hat{\omega}_{bb'} = \left(\sum_{s}\sum_{s' \neq s}\sum_{t} e_{bst}e_{b's't}\right) \Big/ S_1(S_1 - 1)(T_1 - 1)$$

where S_1 is the number of individual states included (15) and $T_1 - 1$ is the number of observations per state in the quasi-differenced data. Next $\omega_{bb'} + \gamma_{bb'}$ is estimated as the average value of $e_{bst}e_{b'st}$ computed over states s and months t. That is ,

$$\widehat{\omega_{bb'} + \gamma_{bb'}} = \left(\sum_{s}\sum_{t} e_{bst}e_{b'st}\right) \Big/ S_1(T_1 - 1)$$

The estimated value of $\gamma_{bb'}$ is then obtained as

$$\hat{\gamma}_{bb'} = \widehat{\omega_{bb'} + \gamma_{bb'}} - \hat{\omega}_{bb'}$$

The estimated values of $\gamma_{bb'}$ and $\omega_{bb'}$ are used to form the full set of covariances of the φ's. This estimated covariance matrix is in turn applied to the quasi-differenced data for the 15 individual states and the national aggregate to yield the GLS estimates of the parameters β_{bj}.

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[7]This procedure differs from that of Parks in that the first observation in each time series is ignored (except as used in quasi-differencing) to avoid computational complexity.

[8]The concept behind the following estimation procedure is to use sample moments to approximate the corresponding unknown population moments.

[9]Since these residuals are from quasi-differenced data, a residual at time t is actually based on raw data from times t and $t + 1$.

ESTIMATION RESULTS

The estimates from the basic model are shown in two parts. First I discuss the estimated elements of the covariance structure, which are computed as intermediate products in the GLS technique described above. These elements are of interest because they may indicate the importance of permitting a more general pattern of covariances in the disturbances. Following this discussion, I present the estimates of the supply parameters β_{bj}.

Estimates of the Covariance Structure

Each autocorrelation coefficient, ρ_b, has a straightforward interpretation as the correlation between a state's basic regression disturbances for Service b (u_{bst}) in two consecutive months. Estimated values of the ρ_b are of moderate size: 0.447 for the Army, 0.385 for the Navy, 0.396 for the Marine Corps, and 0.403 for the Air Force.

The importance of correlations in the national components λ_{bt} and in the state-specific components ϵ_{bst} may be examined in a variety of ways, for these components give rise to a whole host of cross-state and cross-Service correlations. Table 2 gives the estimated correlations of the national components λ_{bt} at a point in time, computed as

$$\mathrm{Corr}(\lambda_{bt}, \lambda_{b't}) = \hat{\omega}_{bb'} \Big/ (\hat{\omega}_{bb}\hat{\omega}_{b'b'})^{1/2}$$

These correlations are fairly large in general and are consistent with the hypothesis that there are omitted factors affecting enlistments in all Services nationwide. Table 3 presents estimated correlations of the state-specific components ϵ_{bst} within states at a point in time, computed as

$$\mathrm{Corr}(\epsilon_{bst}, \epsilon_{b'st}) = \hat{\gamma}_{bb'} \Big/ (\hat{\gamma}_{bb}\hat{\gamma}_{b'b'})^{1/2}$$

Correlations appear to be fairly small and may indicate that omitted state-specific factors tend to have Service-specific effects.

It is also informative to examine the estimated correlations of the new noise φ_{bst}, which is simply the sum of the national component λ_{bt} and the state-specific component ϵ_{bst}. The estimated correlations of the φ_{bst} across states at a point in time, computed as

$$\mathrm{Corr}(\varphi_{bs't}, \varphi_{b'st}) = \hat{\omega}_{bb'} \Big/ \left\{ (\hat{\omega}_{bb} + \hat{\gamma}_{bb})(\hat{\omega}_{b'b'} + \hat{\gamma}_{b'b'}) \right\}^{1/2}$$

Table 2

ESTIMATED CORRELATIONS OF NATIONAL COMPONENTS (λ_{bt}) AT A POINT IN TIME

Service	Army	Navy	Marine Corps	Air Force
Army	1	0.886	0.742	0.633
Navy		1	0.963	0.784
Marine Corps			1	0.787
Air Force				1

Table 3

ESTIMATED CORRELATIONS OF STATE-SPECIFIC COMPONENTS (ϵ_{bst}) WITHIN STATES AT A POINT IN TIME

Service	Army	Navy	Marine Corps	Air Force
Army	1	0.087	0.029	0.142
Navy		1	0.113	0.125
Marine Corps			1	0.130
Air Force				1

where $s \neq s'$, are presented in Table 4. These reflect the importance of the national components λ_{bt} in the φ_{bst}. In particular, the diagonal elements are of the form

$$\hat{\omega}_{bb} \Big/ (\hat{\omega}_{bb} + \hat{\gamma}_{bb})$$

and therefore give the ratio of the estimated variance in λ_{bt} to the estimated variance in φ_{bst}. These values on the diagonal show a moderate degree of cross-state correlation in the new noise φ_{bst} for a particular Service. The generally smaller off-diagonal elements are cross-state correlations in the new noise for different Services.

Table 5 shows the estimated correlations of the new noise φ_{bst} within states at a point in time, computed as

Table 4

ESTIMATED CORRELATIONS OF NEW NOISE (φ_{bst})
ACROSS STATES AT A POINT IN TIME

Service	Army	Navy	Marine Corps	Air Force
Army	0.236	0.167	0.144	0.161
Navy		0.152	0.150	0.160
Marine Corps			0.160	0.165
Air Force				0.274

$$\mathrm{Corr}(\varphi_{bst}, \varphi_{b'st}) = (\hat{\omega}_{bb'} + \hat{\gamma}_{bb'}) \Big/ \left\{ (\hat{\omega}_{bb} + \hat{\gamma}_{bb})(\hat{\omega}_{b'b'} + \hat{\gamma}_{b'b'}) \right\}^{1/2}$$

The values here indicate that moderate cross-Service correlations within a state arise from cross-Service correlations in the national components λ_{bt} and in the state-specific components ϵ_{bst}.[10]

Table 5

ESTIMATED CORRELATIONS OF NEW NOISE (φ_{bst})
WITHIN STATES AT A POINT IN TIME

Service	Army	Navy	Marine Corps	Air Force
Army	1	0.237	0.167	0.267
Navy		1	0.245	0.258
Marine Corps			1	0.266
Air Force				1

[10]Correlations for the u_{bst} across states at a point in time or within states at a point in time can be computed from the relationships $\mathrm{Corr}(u_{bst}, u_{bs't}) = \Theta \cdot \mathrm{Corr}(\varphi_{bst}, \varphi_{bs't})$, where $s \neq s'$, and $\mathrm{Corr}(u_{bst}, u_{b'st}) = \Theta \cdot \mathrm{Corr}(\varphi_{bst}, \varphi_{b'st})$,
where $\Theta = \{(1 - \hat{\rho}_b^2)(1 - \hat{\rho}_{b'}^2)\}^{1/2} / (1 - \hat{\rho}_b \hat{\rho}_{b'})$. Because the estimated values of the autocorrelation coefficients, $\hat{\rho}_b$, are so similar across Services, these correlations are almost identical to those in Tables 4 and 5, respectively. For this reason, the additional correlation matrices are not presented.

Coefficient Estimates

Table 6 gives the GLS estimates of the parameters β_{bj}. Only coefficients of substantive interest are presented. The estimated asymptotic standard error and asymptotic normal statistic appear below each coefficient.

As an aid in interpreting these coefficient estimates, I also assess the effect on yearly enlistments of a hypothetical change in each variable. The population base used in this exercise is the estimated male youth population in March 1983. The hypothetical changes considered are a 1 percent increase in the ratio of military to civilian pay, a 1 percent increase in own-Service's recruiters, the replacement of VEAP with the GI Bill, and an increase of 0.01 in the proportionate deviation of employment from trend. To put the latter hypothetical change in perspective, note that proportionate deviations of employment from trend ranged from a high of 0.036 to a low of −0.051 over the period July 1972 through September 1981. The estimated value for September 1982, however, lies far outside this range at −0.110.[11]

The final row of numbers in each of the four sections of Table 6 translates effects on yearly enlistments into percentage changes in yearly enlistments, using as a base the enlistment levels that would be predicted for FY83 under "normal" business cycle conditions. The latter enlistment levels are 28,083 for the Army,[12] 32,128 for the Navy, 12,742 for the Marine Corps, and 35,222 for the Air Force.[13] For the variables GIBILL, LREC, and LWPAY, the reported percentage changes in enlistments are simply the effects on yearly enlistments given in the row immediately above, divided by the FY83 enlistment levels. For LREC and LWPAY, these percentages therefore have an elasticity interpretation: the percentage change in enlistments resulting from a 1 percent change in recruiters or in the ratio of military to civilian pay. In the case of CYCLE, I report the estimated percentage change in yearly enlistments in moving from a peak to a trough of the business cycle (again relative to the FY83 enlistments predicted under "normal" business cycle conditions). For these purposes, a cyclical

[11]Observations on the proportionate deviation of employment from trend were available only through September 1981. The value for September 1982 was inputed using methods described more fully in Sec. IV below.

[12]As discussed in Sec. IV, this enlistment level pales in comparison with the actual enlistment levels recently achieved by the Army.

[13]These predicted FY83 enlistment levels are shown in Sec. IV as forecasts for an on-trend employment-growth scenario. The forecasts assume that there is no GI Bill, that FY83 recruiter levels are identical with FY82 recruiter levels, that LWPAY in each month of FY83 is the same as in the corresponding month of FY82, and that CYCLE is zero for all of FY83.

Table 6

GENERALIZED LEAST SQUARES ESTIMATES: HIGH SCHOOL DIPLOMA GRADUATE MALES IN AFQT CATEGORIES I-IIIA

Variable	Army	Navy	Marine Corps	Air Force
GIBILL				
Coefficient estimate (×1000)[a]	0.11867	0.08879	0.01597	0.05667
Asymptotic standard error (×1000)	0.01866	0.01536	0.000791	0.02021
Asymptotic normal statistic	6.36	5.78	2.02	2.80
Effect on yearly enlistments of replacing VEAP with GI Bill	14556	10891	1959	6951
% effect on enlistments of replacing VEAP with GI Bill	51.8	33.9	15.4	19.7
LREC				
Coefficient estimate (×1000)[a]	0.19052	0.22215	0.05393	0.23573
Asymptotic standard error (×1000)	0.09902	0.04830	0.06686	0.05869
Asymptotic normal statistic	1.92	4.60	0.81	4.02
Effect on yearly enlistments of 0.01 increase	234	272	66	289
% effect on enlistments of 0.01 (1%) increase	0.833	0.847	0.518	0.821
LWPAY				
Coefficient estimate (×1000)[a]	0.11976	0.17064	0.13170	0.17637
Asymptotic standard error (×1000)	0.08110	0.07389	0.03987	0.08437
Asymptotic normal statistic	1.48	2.31	3.30	2.09
Effect on yearly enlistments of 0.01 increase	147	209	162	216
% effect on enlistments of 0.01 (1%) increase	0.523	0.651	1.27	0.613
CYCLE				
Coefficient estimate (×1000)[a]	−0.37341	−0.84632	−0.37581	−0.44328
Asymptotic standard error (×1000)	0.12860	0.10716	0.05993	0.12775
Asymptotic normal statistic	−2.90	−7.90	−6.27	−3.47
Effect on yearly enlistments of 0.01 increase	−458	−1038	−461	−544
Peak-to-trough change in enlistments as % of normal enlistments	23.8	47.1	52.7	22.5

[a]Reported coefficient estimate is 1000 times the effect of a unit change in the explanatory variable on the monthly enlistment rate. See text for variable definitions.

peak and a cyclical trough are defined by the extreme monthly values (observed or estimated) of CYCLE over the interval July 1972 through September 1982. As noted above, the maximum monthly observed value is 0.036; the minimum is −0.110. The reported percentage change assumes that these values are maintained for the full fiscal year.[14]

It should be emphasized that the enlistment supply model used here does *not* imply constant elasticities, and hence the percentage changes reported in Table 6 depend heavily on the enlistment levels that are used as a base. Predicted levels for FY83, rather than observed levels in some past year, are chosen to make the computations of more current relevance. The base levels use "normal" cyclical conditions, as opposed to cyclical expansions or contractions, in order to abstract from cyclical effects in the computed responses to pay, recruiters, and the GI Bill.

The estimates in Table 6 appear to be plausible. All estimates have the expected sign and most are measured with reasonable precision. Pay effects are generally a bit smaller than anticipated, particularly for the Army, as is the estimated impact of business cycles on Army enlistments. In addition, the large GI Bill effect for the Army should be interpreted with some care. Because VEAP kickers have not been controlled for, and ultra-VEAP kickers probably played only a minor role in determining Army enlistments over the period of observation, it is reasonable to think of the Army's GI Bill effect as computed relative to a VEAP program offering either no or small kickers, not the large ultra-VEAP kickers.

Restricting the Covariances

Because this study permits a more general covariance structure than is commonly used in this literature, it is of interest to know how estimates would be affected by imposing some of the traditional covariance assumptions. For this reason I offer two specializations of the more general model: Restricted Models I and II.

The first of the more restrictive models continues to assume that regression disturbances for each Service and state follow an AR(1) process, but now the national components λ_{bt} are assumed absent. Recall that these national components were introduced to capture unobservable factors that would affect enlistments in all states: changes in a Service's advertising in national media, changes in federally funded

[14]The cyclical peak and cyclical trough enlistment levels used here are the forecast values reported in Sec. IV under the expansionary and recessionary cyclical scenarios.

student loan programs, nationwide changes in attitudes toward the military, changes in a Service's recruiting policy or management, and so forth. By assuming these national components are absent, Restricted Model I rules out any covariance across the disturbances of different states.[15] The state-specific components ϵ_{bst} are still allowed to covary across Services within a state.

Recalculating the model with the previously given values of ρ_b, but with all $\omega_{bb'}$ forced to zero, yields estimated within-state correlations of the state-specific components ϵ_{bst} given in Table 7. Because the national components λ_{bt} are now assumed to be identically zero, the state-specific component ϵ_{bst} is equivalent to the new noise φ_{bst}. (See Eq. (3).) Hence Table 7 also provides the estimated within-state correlations of the φ_{bst}. The method used to estimate the covariance structure forces the entries in Table 7 to coincide with the corresponding entries in Table 5.

The GLS coefficient estimates and related statistics for Restricted Model I are shown in Table 8.[16] Table 9 simplifies the task of comparing across models by presenting the estimated percentage effects from the more general model (Table 6) and from Restricted Model I (Table 8). A comparison with the general model shows that the more restrictive model yields much larger cyclical effects, recruiter effects, and Army pay effects, but a much lower pay effect for the Air Force. Indeed, the Air Force pay effect is too small to be believable, whereas

Table 7

ESTIMATED CORRELATIONS OF STATE-SPECIFIC COMPONENTS (ϵ_{bst}) WITHIN STATES AT A POINT IN TIME
(Restricted Model I)

Service	Army	Navy	Marine Corps	Air Force
Army	1	0.237	0.167	0.267
Navy		1	0.245	0.258
Marine Corps			1	0.266
Air Force				1

[15]Because the national aggregates are weighted cross-state averages, the disturbances in national-level equations are still correlated with the disturbances in each state's equations, and the estimation procedure therefore allows for such correlations.

[16]To facilitate comparisons across models, the percentage effects on enlistments given in Table 8 are computed relative to the same base as in Table 6, i.e., FY83 enlistment levels predicted from the more general model.

Table 8

GENERALIZED LEAST SQUARES ESTIMATES: HIGH SCHOOL DIPLOMA GRADUATE MALES IN AFQT CATEGORIES I-IIIA
(Restricted Model I)[a]

Variable	Army	Navy	Marine Corps	Air Force
GIBILL				
Coefficient estimate (×1000)[b]	0.10617	0.08966	0.01154	0.06422
Asymptotic standard error (×1000)	0.00832	0.00867	0.00409	0.00879
Asymptotic normal statistic	12.76	10.34	2.82	7.31
Effect on yearly enlistments of replacing VEAP with GI Bill	13022	10998	1416	7877
% effect on enlistments of replacing VEAP with GI Bill	46.4	34.2	11.1	22.4
LREC				
Coefficient estimate (×1000)[b]	0.28584	0.31890	0.13621	0.30616
Asymptotic standard error (×1000)	0.04984	0.03210	0.04109	0.02607
Asymptotic normal statistic	5.73	9.93	3.31	11.74
Effect on yearly enlistments of 0.01 increase	351	391	167	376
% effect on enlistments of 0.01 (1%) increase	1.25	1.22	1.31	1.07
LWPAY				
Coefficient estimate (×1000)[b]	0.24656	0.18294	0.13933	0.03846
Asymptotic standard error (×1000)	0.07574	0.07585	0.03808	0.07901
Asymptotic normal statistic	3.26	2.41	3.66	0.49
Effect on yearly enlistments of 0.01 increase	302	224	171	47
% effect on enlistments of 0.01 (1%) increase	1.08	0.697	1.34	0.13
CYCLE				
Coefficient estimate (×1000)[b]	−0.55148	−1.07876	−0.52574	−0.71517
Asymptotic standard error (×1000)	0.12242	0.10598	0.05778	0.11932
Asymptotic normal statistic	−4.50	−10.18	−9.10	−5.99
Effect on yearly enlistments of 0.01 increase	−676	−1323	−645	−877
Peak-to-trough change in enlistments as % of normal enlistments	35.1	60.0	73.7	36.3

[a]Restricted Model I assumes that national components λ_{bt} are absent.

[b]Reported coefficient estimate is 1000 times the effect of a unit change in the explanatory variable on the monthly enlistment rate. See text for variable definitions.

the estimated recruiter effects are implausibly large: an LREC elasticity exceeding unity implies that an increase in the male youth population would reduce enlistments, holding constant the number of recruiters and the remaining explanatory variables.

Restricted Model II follows Restricted Model I in assuming that the national components λ_{bt} are zero. It additionally assumes, however, that serial correlation is absent, i.e., that ρ_b is zero for each Service b. Restricted Model II continues to permit the state-specific component ϵ_{bst} to covary across Services within a state, and therefore this model is estimated with a joint generalized least squares procedure in which there are four equations (one for each Service) linked together through correlation in the ϵ_{bst}. Aside from permitting cross-Service covariance in the ϵ_{bst}, the assumptions underlying Restricted Model II are equivalent to those made in most previous studies, which typically use ordinary least squares on each Service separately. It turns out that

Table 9

COMPARISONS OF ESTIMATED EFFECTS ACROSS MODELS[a]

Variable	Model	Army	Navy	Marine Corps	Air Force
GIBILL: % effect on enlistments of replacing VEAP with GI Bill	General	51.8	33.9	15.4	19.7
	Restricted I	46.4	34.2	11.1	22.4
	Restricted II	33.5	28.0	3.32	19.1
LREC: % effect on enlistments of 0.01 (1%) increase	General	0.833	0.847	0.518	0.821
	Restricted I	1.2[illegible]	1.22	1.31	1.07
	Restricted II	0.840	1.09	1.05	1.02
LWPAY: % effect on enlistments of 0.01 (1%) increase	General	0.523	0.651	1.27	0.613
	Restricted I	1.08	0.697	1.34	0.13
	Restricted II	1.67	0.738	1.19	0.08
CYCLE: Peak-to-trough change in enlistments as % of normal enlistments	General	23.8	47.1	52.7	22.5
	Restricted I	35.1	60.0	73.7	36.3
	Restricted II	44.0	63.1	74.5	36.9

[a]Estimates are from Table 6 for the general model, from Table 8 for Restricted Model I, and from Table 11 for Restricted Model II.

imposing the additional assumption that the ϵ_{bst} are uncorrelated across Services produces estimates that are nearly the same as those reported below for Restricted Model II.

Table 10 provides the estimated within-state correlations of the state-specific components ϵ_{bst} for Restricted Model II. As in Restricted Model I, the state-specific components ϵ_{bst} are equivalent to the new noise φ_{bst}, and thus the figures in Table 10 are also estimated correlations of the φ_{bst} within states at a point in time.

The coefficient estimates and related statistics obtained for Restricted Model II are given in Table 11.[17] The task of comparing results from Restricted Model II with those from the other two models is again simplified by the use of Table 9. The major differences in coefficient estimates for Restricted Model II as compared with Restricted Model I are for the Army, where GI Bill and recruiter effects are substantially reduced and pay and cyclical effects are substantially increased. In addition, the GI Bill effect for the Marine Corps is now so small as to be virtually nonexistent. Although smaller than in Restricted Model I, estimated recruiter effects remain large in general. The estimated pay effect for the Air Force is again implausibly small. Finally, the reported standard errors appear to be quite small in general, but these standard errors are meaningless if in fact there are serial correlations or cross-state correlations in the disturbances, as the more general model suggests there are.

The estimation results from the more restrictive models illustrate that assumptions concerning the covariance structure of the disturbances do indeed matter. Many coefficient estimates and standard

Table 10

ESTIMATED CORRELATIONS OF STATE-SPECIFIC COMPONENTS (ϵ_{bst}) WITHIN STATES AT A POINT IN TIME
(Restricted Model II)

Service	Army	Navy	Marine Corps	Air Force
Army	1	0.174	0.088	0.223
Navy		1	0.291	0.298
Marine Corps			1	0.302
Air Force				1

[17]Percentage effects on enlistments given in Table 11 are again computed off of the base used in Table 6, i.e., FY83 enlistments predicted from the more general model.

Table 11

GENERALIZED LEAST SQUARES ESTIMATES: HIGH SCHOOL DIPLOMA GRADUATE MALES IN AFQT CATEGORIES I-IIIA
(Restricted Model II)[a]

Variable	Army	Navy	Marine Corps	Air Force
GIBILL				
Coefficient estimate ($\times 1000$)[b]	0.07659	0.07330	0.00344	0.05474
Asymptotic standard error ($\times 1000$)	0.00604	0.00662	0.00304	0.00658
Asymptotic normal statistic	12.68	11.07	1.13	8.31
Effect on yearly enlistments of replacing VEAP with GI Bill	9395	8990	423	6714
% effect on enlistments of replacing VEAP with GI Bill	33.5	28.0	3.32	19.1
LREC				
Coefficient estimate ($\times 1000$)[b]	0.19279	0.28499	0.10903	0.29325
Asymptotic standard error ($\times 1000$)	0.03304	0.02274	0.02975	0.01837
Asymptotic normal statistic	5.84	12.53	3.66	15.96
Effect on yearly enlistments of 0.01 increase	236	350	134	360
% effect on enlistments of 0.01 (1%) increase	0.840	1.09	1.05	1.02
LWPAY				
Coefficient estimate ($\times 1000$)[b]	0.38313	0.19359	0.12398	0.02200
Asymptotic standard error ($\times 1000$)	0.06176	0.06239	0.03108	0.06456
Asymptotic normal statistic	6.20	3.10	3.99	0.34
Effect on yearly enlistments of 0.01 increase	470	237	152	27
% effect on enlistments of 0.01 (1%) increase	1.67	0.738	1.19	0.08
CYCLE				
Coefficient estimate ($\times 1000$)[b]	-0.69143	-1.13453	-0.53146	-0.72642
Asymptotic standard error ($\times 1000$)	0.07919	0.07251	0.03987	0.08090
Asymptotic normal statistic	-8.73	-15.65	-13.33	-8.98
Effect on yearly enlistments of 0.01 increase	-848	-1392	-652	-891
Peak-to-trough change in enlistments as % of normal enlistments	44.0	63.1	74.5	36.9

[a]Restricted Model II assumes that national components λ_{bt} are absent and that disturbances are uncorrelated over time.

[b]Reported coefficient estimate is 1000 times the effect of a unit change in the explanatory variable on the monthly enlistment rate. See text for variable definitions.

errors are sensitive to these assumptions. The more general model replaces the restrictive assumptions about covariances that are commonly made in the literature with estimates derived from the data. These estimates are both plausible and large enough to indicate that the more general model is to be preferred.

It should also be noted, however, that parameter estimates for the more general model may differ from estimates in previous work for reasons other than differences in method of estimation. In particular, Restricted Model II uses covariance assumptions that are traditional in this literature but obtains some estimates that are atypical. I suspect that the source of these differences is in the choice of variables. Recall that this study, unlike most other studies in this literature dealing with data having cross-sectional content, includes a separate intercept for each state. In addition, and perhaps more importantly, position in the business cycle is here measured by proportionate deviations of employment from trend rather than the more traditional unemployment rate. If CYCLE is a better reflection of position in the business cycle, it should not be surprising to find larger estimated cyclical responses in Restricted Model II than are usually found, despite similarities in methods of estimation.

SUMMARY

Section III has presented estimation results for a general model of enlistment supply, one which allows for covariances in disturbances across Services, across states, and over time. It also has given comparable results for two restrictive models, closer in form to the models commonly estimated, in which various of these covariances are assumed to be zero. The correlations in disturbances estimated in the general model are usually moderate in size. In general, ignoring such covariances can be expected to result in inefficient estimation, i.e., estimation yielding larger true standard errors. Reported standard errors are much smaller for the restricted models, however, because the calculated standard errors incorrectly ignore the covariance structure. Thus, standard errors reported by other researchers who assume away all covariances are likely to give an erroneous impression of the precision of the associated coefficient estimates.

Perhaps more important than the problem of standard errors is the apparently large effect that a more general specification of the error structure can have on coefficient estimates. Although there is no reason to expect bias in the coefficients derived from the more restrictive models, the actual changes that occur when restrictions are introduced

are quite striking. Because the data suggest that such restrictions are unwarranted, there is a presumption that the coefficients derived from the more general model are likely to be closer to the true underlying supply parameters.

IV. FORECASTING METHODOLOGY, ASSUMPTIONS, AND RESULTS

The general model presented in the preceding sections is now used to predict enlistments on a fiscal year basis for the final half of FY81 and for FY82 through FY90, both by Service and the Department of Defense as a whole. These forecasts are made under certain assumptions regarding the future behavior of the explanatory variables. Before offering these assumptions and the forecasts themselves, I briefly discuss the forecasting methodology.

METHODOLOGY

The forecasting technique employed here is one that yields best (minimum mean square prediction error) linear unbiased predictions, conditional on the assumed values of the explanatory variables and on the covariance matrix of the disturbances. This method is discussed in the seminal work of Goldberger (1962) and, in somewhat more general form, in Theil (1971, Chap. 6). The first step is to predict monthly enlistment rates for each Service at the national level:

$$\hat{y}_{bnt} = \sum_j x_{bntj} \hat{\beta}_{bj} + \hat{\rho}_b^{\,t-T_1} \hat{u}_{bnT_1} \tag{6}$$

where $\hat{y}_{bnt}$ is the predicted enlistment rate at the national level for Service b at future time t; x_{bntj} is the assumed value of the jth explanatory variable for Service b at the national level at future time t; $\hat{\beta}_{bj}$ is the GLS estimate of β_{bj}; $\hat{\rho}_b$ is the estimated value of the autocorrelation coefficient ρ_b; $t - T_1$ is the number of months between forecast period t and the final period of observation T_1; and $\hat{u}_{bnT_1}$ is the national-level residual at time T_1 defined by

$$\hat{u}_{bnT_1} = y_{bnT_1} - \sum_j x_{bnT_1j} \hat{\beta}_{bj}$$

The predicted enlistment rates are composed of two parts, which may be conveniently viewed in terms of Eq. (1). The first term on the right-hand side of Eq. (6), corresponding to the deterministic portion of Eq. (1), is the hypothesized future value of the explanatory variables multiplied by GLS coefficient estimates. The second term, corresponding to the disturbance term in Eq. (1), is the expected value of the

future disturbance given the estimated value of the disturbance in the final observation period. Because there is serial correlation in the disturbances, past values of the disturbances are informative about future values, and efficient forecasts use this information. These predicted monthly enlistment rates are then multiplied by the youth population in the appropriate month, summed across months of the fiscal year, and, when obtaining Department of Defense totals, summed across Services.

The standard errors reported for these forecasts are also conditional on the estimated covariance structure of the disturbances and the hypothesized values of the explanatory variables.[1] Two basic sources of uncertainty in the predicted monthly enlistment rates are accounted for. First, the $\hat{\beta}_{bj}$ used in constructing both the deterministic portion of the forecast and the predicted future disturbances (via their use in estimating past disturbances) are subject to estimation errors, and both the variances in and covariances among these estimation errors are recognized in the reported standard errors. Second, full account is taken of the covariance structure of the disturbances and, in particular, the degree of predictability of future disturbances from knowledge of past disturbances. Because predicted monthly enlistment levels are summed to form fiscal year totals, reported standard errors have been calculated to reflect both the standard errors of the individual monthly forecasts and the correlation across the monthly forecast errors. Standard errors for DoD totals take account of errors in forecasts for the individual Services, as well as cross-Service covariance in forecast errors.

ASSUMPTIONS

Although all forecasts reported here are conditional on values of the explanatory variables, the extent to which these values are actually known varies across subintervals of the forecast period. For the final six months of FY81, the values all of the explanatory variables are observed. For FY82, most data series are incomplete, but values are imputed from closely related series. For FY83 and beyond, assumptions about the explanatory variables are based on past behavior of these same variables, and these assumptions are necessarily of a more speculative nature.

The assumptions and imputation procedures used for FY82 and beyond are as follows:

[1]Additional technical details on the forecasting method, and on the computation of forecast standard errors in particular, may be found in App. B.

- The projected population of male youth in July of each forecast year was obtained from Current Population Reports (U.S. Bureau of the Census, 1977) and linearly interpolated to form a monthly series. These figures are used in constructing the recruiter intensity variables and in translating enlistment rates into enlistment levels.
- Recruiter levels observed for the first half of FY82 are assumed to remain unchanged over the entire forecast period.
- The GI Bill was not available to enlistees in FY82, and it is assumed to remain unavailable in the future.
- The ratio of military to civilian pay in FY82 was obtained from actual RMC figures and imputed civilian wages.[2] The estimated ratio for each month in FY82 is assumed to apply to the corresponding month in each of the remaining fiscal years.
- Values of the theoretically correct cyclical variable (the population-weighted average of the states' proportionate deviations of employment from trend) were unavailable for FY82, but again a closely related series was available for imputation.[3] For FY83 and beyond, values of the cyclical variable are unknown, and any forecasts of this variable would necessarily be fraught with at least as much uncertainty as typically accompanies predictions of aggregate economic activity. Therefore, rather than considering only a single cyclical scenario, four alternative cyclical scenarios are entertained, and predicted enlistment levels are provided for each scenario. These scenarios may be thought of as an expansionary scenario, an

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[2]Imputation of civilian wages for FY82 was necessary because the theoretically correct national-level variable (the population-weighted average of the logarithm of state-level average weekly earnings in manufacturing) was unavailable. Imputations were carried out by regressing the theoretically correct variable on month dummies and a strongly related series, the logarithm of average hourly earnings of manufacturing production workers at the national level (as reported by the Bureau of Labor Statistics). The observation interval for this regression was July 1972 through September 1981. Since OLS residuals displayed substantial first-order serial correlation, it was assumed that the disturbances followed an AR(1) process, and a GLS procedure was used in computing coefficient estimates and in forecasting the civilian wage series for FY82.

[3]In this case, the related series was the proportionate deviation of national employment from trend. More specifically, the latter deviations were calculated as the actual logarithm of national employment minus the predicted logarithm of national employment, where the predicted logarithm of national employment was obtained from an OLS regression of the logarithm of national employment on month dummies, time, and time squared, over the interval 1952 through 1981. Using data from July 1972 through September 1981, an OLS regression of the theoretically correct variable on these deviations, trend, and an intercept gave evidence of substantial first-order serial correlation in the disturbances. A GLS procedure permitting an AR(1) process in the disturbances was used to estimate the coefficients and to provide predicted values of the cyclical variable for FY82.

on-trend employment-growth scenario, a recessionary scenario, and, finally, a scenario linked to Data Resources' forecast of future unemployment rates. These scenarios are discussed in turn.

Cyclical Scenarios

The expansionary cyclical scenario assumes that CYCLE is 0.0357 for each month in FY82 and beyond, an assumption consistent with employment continually lying about 3.6 percent above trend in each state. This particular value of CYCLE was attained in June 1973 and is the highest monthly value recorded over the period for which this variable could be observed (July 1972 through September 1981). In June of 1973 the seasonally adjusted aggregate unemployment rate was 4.8 percent. For FY82 this assumed value of CYCLE is clearly counterfactual, but the assumption is maintained to facilitate comparisons with other scenarios.

The on-trend employment-growth scenario assumes that CYCLE is zero for each month in FY82 and beyond, i.e., that employment is continuously on trend. This value of CYCLE is quite close to the average value observed over the interval July 1972 through September 1981 (0.000018), a period during which the aggregate unemployment rate averaged 6.6 percent. Once again, this assumption is counterfactual for FY82 but is made to facilitate comparisons.

In the recessionary cyclical scenario, observed (estimated) values of CYCLE are used for FY82. For each month of FY83 and beyond, CYCLE is assumed to be −0.110, an assumption consistent with employment continuously lying about 12 percent below trend in each state. This figure is the estimated value of CYCLE in September 1982 and is substantially lower than the minimum value of CYCLE recorded over the observation interval, July 1972 through September 1981. The minimum over the latter interval is −0.051 and was attained in September 1981. From September of 1981 to September of 1982, the economy continued to slide downhill, with the aggregate unemployment rate rising from 7.6 percent to 10.1 percent. Hence, the estimated value of CYCLE for September 1982 is chosen to give an indication of expected enlistment levels in recessionary times such as those currently being experienced.

The fourth scenario again uses observed (estimated) values of CYCLE for FY82. Beginning in calendar year 1983, however, the aggregate unemployment rate in any month is assumed to be the calen-

dar year average predicted by Data Resources, Incorporated (DRI).[4] The DRI unemployment rate forecast indicates that the economy is expected to ease out of the current recession gradually and to approach roughly "normal" times by 1990. To incorporate the DRI forecast, it was necessary to link CYCLE with the unemployment rate. Such a link was provided by regressing CYCLE on the seasonally adjusted aggregate unemployment rate and month dummies over the interval July 1972 through September 1981. Since OLS residuals indicated substantial first-order serial correlation, a GLS procedure permitting an AR(1) process in the disturbances was used in estimation and in predicting values of CYCLE.[5]

FORECASTS

Table 12 compares observed enlistments with forecasted enlistments for the final half of FY81 and for FY82.[6] Figures in the left half of the table show that the model underpredicts enlistments for the final six months of FY81 in all Services. The extent of underprediction is fairly modest, however, and for each Service the actual value is well within a two-standard-error band around the forecast value.

In the right half of Table 12, FY82 forecasts are compared with preliminary enlistment counts for FY82. These preliminary counts are expected to be somewhat higher than final counts comparable with the projection figures because the preliminary numbers do not allow for attrition from the Delayed Entry Program (DEP) and because they assume that enrolled high school seniors will receive their high school diplomas. Nonetheless, it appears that projections are somewhat too high for the Air Force and too low for the other Services, with particularly severe underprediction for the Army.[7]

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[4]For the final three months of calendar year 1982, the recessionary value of CYCLE is assumed to hold.

[5]The relationship between CYCLE and the unemployment rate is of some interest. The GLS estimates are, in part,

$$\underset{(3.49)}{\text{CYCLE} = 0.043} - \underset{(6.36)}{0.0082\text{UR}} + \text{month effects},$$

where UR is the unemployment rate. Asymptotic normal statistics are in parentheses.

[6]Observed and predicted enlistments over the observation interval are compared in Table A.2 of App. A.

[7]FY82 forecasts from Restricted Models I and II showed the same pattern in that these models overpredicted (but by more) for the Air Force and underpredicted (but by less) for the remaining three Services. In view of the larger estimated cyclical responses in these models, it is not surprising that the FY82 forecasts from these models are larger than those from the more general model. One must wonder whether these models would predict well in a year more typical than FY82.

Table 12

ENLISTMENTS OF HIGH SCHOOL DIPLOMA GRADUATE MALES IN AFQT CATEGORIES I-IIIA: A COMPARISON OF REALIZED VALUES WITH FORECASTS

	Final 6 Months of FY81			FY82		
Service	Actual	Forecast[a]	% Error[b]	Preliminary Count	Forecast[a]	% Error[b]
Army	15352	13328 (1394)	−13.2	52200	31856 (3112)	−39.0
Navy	19893	18530 (1077)	−6.9	44200	40542 (1958)	−8.3
Marine Corps	7517	7047 (564)	−6.3	19200	16576 (1038)	−13.7
Air Force	19759	19367 (1483)	−2.0	37400	39720 (2520)	6.2

[a]Forecasts assume actual or estimated values for all explanatory variables. Standard error of prediction is in parentheses.
[b](Forecast minus actual)/actual.

Part of the problem in the Army case for FY82 may be that this model fails to allow any role for the Army's ultra-VEAP kicker program. The latter program, available over the entire country in FY82, may have had some effect on Army enlistments, although experimental results suggest that the effect would not be large enough to account for much of the underprediction. A second source of underprediction for the Army, and perhaps for the Navy and the Marine Corps as well, may lie in the business cycle conditions of FY82. The cyclical downturn in FY82 was severe when judged against cyclical conditions over the period of estimation, and it is possible that parameters estimated over this latter regime of fairly mild cyclical fluctuations are inappropriate for extreme cyclical movements.

Although the extent of underprediction in FY82 for the Army, and perhaps for the Marine Corps as well, is somewhat troublesome, I do not consider the problem to be so critical as to suggest rejection of the model. The predictions for these two Services in the final half of FY81 are much closer to the mark. In addition, FY82 appears to have been aberrant in that enlistments in these two Services far outdistanced the fiscal year totals in any other year since the expiration of the GI Bill. It is difficult to imagine a plausible set of parameter values for the included variables (that is, aside from the potential difficulties noted above) that would explain FY82 enlistments, particularly for the Army,

and at the same time be capable of forecasting enlistments during the more normal times that would be expected to dominate the future.

Forecasts for the interval FY82 through FY90 are presented in Tables 13 through 16. Within each scenario other than the DRI-based scenario, all changes in enlistments over time stem solely from the decline in the male youth population. This population decline is manifested in two ways. First, an unchanging enlistment rate would imply declining enlistment levels as the population base shrinks. Second, as the population declines, recruiter intensity rises to reflect an increase in recruiter contacts per potential enlistee. This increase in recruiter

Table 13

FORECASTS OF ENLISTMENTS OF HIGH SCHOOL DIPLOMA GRADUATE MALES IN AFQT CATEGORIES I-IIIA BY FISCAL YEAR[a]
(DRI Unemployment Rate Scenario)

Fiscal Year	Army	Navy	Marine Corps	Air Force	DoD Total[b]
1982	31856	40542	16576	39720	128694
	(3112)	(1958)	(1038)	(2520)	(6858)
1983	30914	38544	15591	38582	123631
	(3201)	(1811)	(963)	(2381)	(6760)
1984	29591	35730	14227	36990	116539
	(3369)	(1669)	(962)	(2266)	(6767)
1985	29046	34708	13661	36319	113735
	(3570)	(1640)	(1063)	(2259)	(6981)
1986	28600	33911	13210	35769	111491
	(3753)	(1637)	(1186)	(2274)	(7224)
1987	28321	33418	12934	35426	110099
	(3867)	(1643)	(1271)	(2292)	(7389)
1988	28167	33096	12780	35244	109287
	(3893)	(1641)	(1288)	(2296)	(7417)
1989	27999	32758	12614	35038	108408
	(3933)	(1643)	(1317)	(2304)	(7472)
1990	27833	32489	12456	34829	107608
	(4013)	(1654)	(1382)	(2323)	(7602)

[a]Standard error of forecast is given in parentheses.
[b]DoD total may not equal sum across Services because of rounding.

intensity over time raises the enlistment rate, thereby tending to offset the first effect of a declining population base. The first of these effects dominates, however, resulting in the patterns of declining enlistments for FY83 through FY90 depicted in Tables 14 through 16.

The forecasts in Tables 14 through 16 are of interest because they isolate the effects of declining population, and by comparing across tables they demonstrate the importance of business cycle fluctuations. For policy purposes, however, the DRI-based forecasts of Table 13 are of special interest because the cyclical assumptions underlying these forecasts are more plausible. These forecasts show falling enlistments over time, both because of the aforementioned decline in youth popula-

Table 14

FORECASTS OF ENLISTMENTS OF HIGH SCHOOL DIPLOMA GRADUATE MALES IN AFQT CATEGORIES I-IIIA BY FISCAL YEAR[a]
(Recessionary Scenario)

Fiscal Year	Army	Navy	Marine Corps	Air Force	DoD Total[b]
1982	31856	40542	16576	39720	128694
	(3112)	(1958)	(1038)	(2520)	(6858)
1983	33109	43518	17800	41188	135615
	(3354)	(2166)	(1148)	(2733)	(7348)
1984	32808	43022	17465	40809	134104
	(3487)	(2118)	(1149)	(2680)	(7446)
1985	32479	42488	17116	40394	132476
	(3636)	(2083)	(1198)	(2643)	(7603)
1986	32165	41990	16798	40001	130953
	(3777)	(2063)	(1275)	(2622)	(7784)
1987	31966	41680	16602	39753	130001
	(3864)	(2056)	(1333)	(2615)	(7909)
1988	31933	41630	16570	39714	129847
	(3880)	(2055)	(1343)	(2614)	(7932)
1989	31868	41526	16507	39630	129532
	(3907)	(2054)	(1363)	(2613)	(7974)
1990	31715	41289	16363	39438	128806
	(3971)	(2052)	(1411)	(2611)	(8073)

[a]Standard error of forecast is given in parentheses.
[b]DoD total may not equal sum across Services because of rounding.

Table 15

FORECASTS OF ENLISTMENTS OF HIGH SCHOOL DIPLOMA GRADUATE MALES IN AFQT CATEGORIES I-IIIA BY FISCAL YEAR[a]
(On-Trend Employment-Growth Scenario)

Fiscal Year	Army	Navy	Marine Corps	Air Force	DoD Total[b]
1982	28196	32245	12892	35374	108706
	(3110)	(1651)	(870)	(2251)	(6415)
1983	28083	32128	12742	35222	108175
	(3261)	(1622)	(889)	(2240)	(6527)
1984	27932	31969	12557	35020	107478
	(3449)	(1605)	(964)	(2242)	(6720)
1985	27755	31782	12361	34786	106684
	(3645)	(1604)	(1082)	(2260)	(6971)
1986	27578	31593	12181	34555	105906
	(3820)	(1617)	(1210)	(2288)	(7231)
1987	27461	31470	12069	34406	105406
	(3926)	(1631)	(1295)	(2310)	(7402)
1988	27442	31452	12050	34383	105328
	(3944)	(1633)	(1309)	(2314)	(7432)
1989	27403	31408	12014	34330	105156
	(3977)	(1638)	(1336)	(2321)	(7487)
1990	27311	31307	11931	34210	104759
	(4052)	(1652)	(1400)	(2339)	(7617)

[a]Standard error of forecast is given in parentheses.
[b]DoD total may not equal sum across Services because of rounding.

tion and because of expected improvements in the aggregate economy embedded in the DRI unemployment rate forecasts.

Although the patterns of declining enlistments over time depicted in Tables 13 through 16 do not seem implausible, some care should be exercised in interpreting the results. As noted above, youth population size has a role in this model only through its effect on recruiter intensity and through the mechanical relationship between enlistment rates and enlistment levels. In particular, what is ignored is the effect of cohort size on civilian earnings. While in some sense this problem has been avoided by assuming that the ratio of military to civilian pay remains constant over time, the latter assumption is not innocuous if

Table 16

FORECASTS OF ENLISTMENTS OF HIGH SCHOOL DIPLOMA GRADUATE MALES IN AFQT CATEGORIES I-IIIA BY FISCAL YEAR[a]
(Expansionary Scenario)

Fiscal Year	Army	Navy	Marine Corps	Air Force	DoD Total[b]
1982	26508	28420	11194	33371	99493
	(3277)	(1720)	(917)	(2352)	(6578)
1983	26437	28395	11085	33267	99184
	(3426)	(1692)	(949)	(2345)	(6689)
1984	26334	28348	10949	33123	98754
	(3611)	(1673)	(1033)	(2352)	(6879)
1985	26207	28273	10803	32949	98233
	(3802)	(1671)	(1155)	(2373)	(7125)
1986	26074	28186	10668	32770	97699
	(3973)	(1682)	(1284)	(2402)	(7381)
1987	25985	28125	10583	32653	97347
	(4077)	(1695)	(1368)	(2424)	(7548)
1988	25971	28117	10569	32636	97293
	(4094)	(1697)	(1382)	(2428)	(7577)
1989	25940	28092	10542	32594	97168
	(4126)	(1702)	(1409)	(2435)	(7631)
1990	25868	28036	10478	32497	96879
	(4200)	(1714)	(1472)	(2454)	(7759)

[a]Standard error of forecast is given in parentheses.
[b]DoD total may not equal sum across Services because of rounding.

the smaller youth cohorts in the future fare much better in the civilian labor market than have the larger cohorts in the past. In this case, maintaining a constant ratio of military to civilian pay may require military pay to increase much more rapidly in real terms than it has in the past.[8] While I believe it important to grapple with this issue, doing

[8]Using youth wages in the basic model would not help to resolve this issue. The problem would still be to predict youth wages in the future. This cohort size question does suggest, however, that the ratio of military pay to the pay of manufacturing production workers in the *future* may not provide a reliable guide to *future* pay policies if youth wages increase more rapidly than wages of older individuals. In such a case, the ratio of military pay to youth pay (the latter presumably being measured at the national level)

so would go far beyond the bounds of this report and would require a study in itself.[9]

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would become more relevant, and the investigation of alternative pay policies would use the estimated pay effect given here in conjunction with the latter pay ratio. This procedure assumes, of course, that cohort size effects have not been important enough over the *estimation* period to alter the proportionate relationship between youth wages and wages of manufacturing production workers. The latter assumption seems reasonable.

[9]Estimates of the wage effects of declining cohort size are given in Tan and Ward (1984).

V. SUMMARY AND CONCLUSIONS

The model discussed in this report differs from most previous forecasting models in the choice of variables and in the specification of the covariance structure of the disturbances, with resulting differences in methods of estimation and forecasting. With regard to the choice variables, this study, unlike most other enlisted supply studies using data with cross-sectional content, permits individual intercepts for each cross-sectional unit, thereby allowing for permanent cross-state differences that are correlated with the remaining explanatory variables. In addition, position in the business cycle is measured by the proportionate deviation of employment from trend rather than the commonly used unemployment rate. These differences in variable specification appear to matter: when the model is estimated in more traditional ways, the business cycle appears to be an extraordinarily critical supply factor.

The assumptions regarding the covariance structure also appear to be important. Estimating the model using more restrictive assumptions (which are commonly made implicitly in this literature) produces parameter estimates and standard errors that are sometimes quite different from those produced in the general model. Assuming, as I do, that the more general covariance structure is substantially more realistic, the advantages of taking account of these covariances in estimation and forecasting are to increase the true precision of the estimates and forecasts and to provide more accurate standard errors on estimates and forecasts. For this reason, I believe the reported standard errors from the general model to be superior indicators of the uncertainty surrounding the estimates relative to the standard errors reported in previous studies. For forecasts, my approach treats standard errors as conditional on the future course of the explanatory variables, which is in turn a major source of uncertainty that is unaccounted for here and in other studies as well.

Despite these differences in explanatory variables and in estimation methods, the effects found in the general model are within the range of estimates obtained in past work on enlisted supply. Because there is a vast array of previous studies, however, this observation is not terribly surprising. The ratio of military to civilian pay matters, although apparently less for the Army than one might expect. The enlistment rate moves countercyclically, other things the same, with especially large cyclical sensitivity observed for the Navy and the Marine Corps.

Finally, recruiter intensity and the level of postservice educational benefits (as represented by the GI Bill) are also important determinants of supply behavior.

Forecasts from the model for the final half of FY81 are reasonably close to the actual values. For FY82, predictions are especially wide of the mark for the Army, indicating the need for additional work on this Service in particular. It seems likely that one source of FY82 underprediction for the Army is failure to obtain an effect for the Army's ultra-VEAP kickers. Reestimating the model with FY82 data included may attribute some of the Army's unusually high FY82 enlistments to this program. In addition, it is possible that the relevant supply parameters change when the economy moves into a serious cyclical downturn such as that which characterized FY82. Investigation of this possibility is again an item for future research.

The major message from the enlistment forecasts based on the DRI unemployment rate scenario is that enlistments are likely to decline substantially over the remainder of the decade as the economy gradually returns to normal and as the population of young males shrinks over time. If the smaller cohorts of young males in the future enjoy special success in the labor market, the decline in enlistments forecast here will probably prove to be optimistic unless military pay for first-termers is permitted to keep pace with private sector pay for youth.

This research has raised a number of problems that should be addressed in future work. First, cross-state differences in the size of the youth population may cause the disturbances to be heteroskedastic at the individual state level, and it would be useful to allow for this possibility in estimation. Second, effects of educational benefit programs such as VEAP kickers have been ignored in the current work. It would be worthwhile to explore various methods of introducing these effects, either by linking all educational benefits programs together using their expected dollar benefits to enlistees or by using experimental results in a mixed estimation scheme. Third, the role of recruiters and recruiter incentives deserve additional attention. As better cross-sectional data on recruiters become available, it may be possible to estimate simultaneously the cross-sectional determinants of both recruiter allocations and enlistments. Finally, for forecasting into the more distant future, it may be important to consider future demographic changes that will alter the quality composition of youth cohorts.

Appendix A

SUMMARY STATISTICS

Table A.1

MEANS OF SELECTED VARIABLES AT THE NATIONAL LEVEL
BY FISCAL YEAR

	1975[a]	1976	1977	1978	1979	1980	1981[b]
Monthly enlistment rate (×1000)							
Army I-IIIA	0.44585	0.34983	0.26482	0.19015	0.16391	0.19508	0.22679
Navy I-IIIA	0.44275	0.36621	0.31201	0.23012	0.20468	0.27507	0.28423
Marine Corps I-IIIA	0.18388	0.14341	0.11163	0.09248	0.07841	0.10601	0.11588
Air Force I-IIIA	0.38212	0.33239	0.31407	0.23030	0.21528	0.30385	0.30675
Army IIIB	0.22208	0.19221	0.13955	0.10944	0.09258	0.09584	0.11251
Navy IIIB	0.12012	0.11967	0.10882	0.08174	0.07721	0.09637	0.10083
Marine Corps IIIB	0.06537	0.06166	0.05388	0.04861	0.04488	0.05397	0.05999
Air Force IIIB	0.10901	0.08725	0.09962	0.08357	0.08830	0.12774	0.11439
LREC							
Army	−7.67780	−7.75281	−7.76143	−7.80392	−7.80541	−7.71557	−7.67017
Navy	−7.89161	−8.07039	−8.06556	−8.06062	−8.03927	−7.93766	−7.92281
Marine Corps	−8.50182	−8.54639	−8.59219	−8.60488	−8.59017	−8.53665	−8.53272
Air Force	−8.55044	−8.75098	−8.78096	−8.79365	−8.78472	−8.62924	−8.56085
LWPAY	−0.38581	−0.43097	−0.45926	−0.47614	−0.50110	−0.50569	−0.47245
CYCLE	−0.01311	−0.01878	−0.01380	0.00655	0.01640	−0.00459	−0.02408

[a]For purposes of this table, fiscal year 1975 is defined as October 1974 through September 1975; fiscal year 1976 is defined as October 1975 through September 1976.

[b]Statistics for fiscal year 1981 include data from October 1980 through March 1981 only.

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Table A.2

PREDICTED ENLISTMENTS OF HIGH SCHOOL DIPLOMA GRADUATE MALES IN AFQT CATEGORIES I-IIIA OVER THE OBSERVATION INTERVAL BY FISCAL YEAR[a]

Fiscal Year	Army	Navy	Marine Corps	Air Force
1975[b]	54637	54614	22563	46780
	(54539)	(54172)	(22496)	(46735)
1976	45210	45768	18515	40443
	(43536)	(45591)	(17840)	(41390)
1977	34881	39992	14347	41424
	(33516)	(39492)	(14128)	(39756)
1978	23430	29733	11734	31030
	(24392)	(29523)	(11868)	(29545)
1979	21327	28024	11173	29372
	(21063)	(26302)	(10076)	(27664)
1980	24364	32972	12429	35031
	(24964)	(35199)	(13566)	(38883)
1981	13756	18811	7005	19613
(first six months)	(14448)	(18107)	(7383)	(19541)

[a]Actual enlistments are in parentheses below the predicted value. Unlike the predictions for the forecast interval presented in other tables, these predictions use only the deterministic portion of Eq. (1).

[b]For purposes of this table, fiscal year 1975 is defined to run from October 1974 through September 1975; fiscal year 1976 is defined to run from October 1975 through September 1976.

Appendix B

ESTIMATION AND FORECASTING PROCEDURES

This appendix provides technical details on the estimation and forecasting procedures used in this report. In the first subsection it is demonstrated that replacing observations from the aggregate state (composed of 36 states) with observations at the national level has no effect on the resulting estimates or forecasts.[1] The second subsection gives the GLS coefficient estimator and its covariance matrix. The third subsection discusses the GLS predictor and the covariance matrix of forecast errors.

REPLACING STATE DATA WITH AGGREGATE DATA

By choosing some arbitrary way in which to order the data by states, Services, and time periods, the enlistment equation Eq. (1) may be written in matrix form as

$$Y_1^* = X_1^* \beta + U_1^* \tag{B.1}$$

where the elements of Y_1^* are the y_{bst}, the elements of X_1^* are the x_{bstj}, the elements of U_1^* are the u_{bst}, and the elements of β are the β_{bj}. All months over the period of observation are included in Eq. (B.1). States included in Eq. (B.1) are 15 individual states and a 16th aggregate state, which is composed of the remaining 36 states.[2]

At any point in time, the national enlistment rate for any Service is a weighted average of the state-specific enlistment rates for that Service, where each state's weight is the proportion of male youth residing in that state. Hence, the enlistment rate equation at the national aggregate level, analogous to Eq. (1) at the state level, is

[1]There is a simpler and more elegant proof of this proposition that relies on the best linear unbiasedness of the GLS estimator and predictor. I have instead used the alternative demonstration given here because it seems more instructive.

[2]The relevant variances and covariances for the aggregate state differ from those given in the text for individual states simply because of aggregation. These differences are not spelled out here.

$$y_{bnt} = \sum_j x_{bntj}\beta_{bj} + u_{bnt} \tag{B.2}$$

where
$$y_{bnt} = \sum_s r_{st} y_{bst}$$

$$x_{bntj} = \sum_s r_{st} x_{bstj}$$

$$u_{bnt} = \sum_s r_{st} u_{bst}$$

and where r_{st} is the proportion of male youth at time t residing in state s and the n subscript denotes a national aggregate. For current purposes, the above summations over s run over the 15 individual states and the 16th aggregate state.

Equation (B.2) holds for any month of the observation interval (in the sample range) or the forecast interval (outside the sample range). The national aggregates that are to be forecast may therefore be expressed in matrix form as

$$Y_2 = X_2\beta + U_2 \tag{B.3}$$

where Y_2 contains the future, monthly, national aggregate enlistment rates that are to be predicted; X_2 contains the hypothetical national-level values of the explanatory variables over the forecast interval; and U_2 contains the national aggregate disturbances over the forecast interval. The covariance relationships between the elements of U_1^* and U_2 are given by

$$E\begin{pmatrix} U_1^* \\ U_2 \end{pmatrix}(U_1^{*\prime}\ U_2^{\prime}) = \sigma^2 \begin{pmatrix} V_{11}^* & V_{21}^{*\prime} \\ V_{21}^* & V_{22}^* \end{pmatrix} = \sigma^2 V^* \tag{B.4}$$

Given known or estimated values of the elements of V^* in Eq. (B.4), the GLS estimator of β, say $\tilde{\beta}$, is given by

$$\tilde{\beta} = (X_1^{*\prime} V_{11}^{*-1} X_1^*)^{-1} X_1^{*\prime} V_{11}^{*-1} Y_1^* \tag{B.5}$$

with estimated covariance matrix, $\sum_{\tilde{\beta}\tilde{\beta}}$, given by

$$\textstyle\sum_{\tilde{\beta}\tilde{\beta}} = \tilde{\sigma}^2(X_1^{*\prime} V_{11}^{*-1} X_1^*)^{-1} \tag{B.6}$$

where
$$\tilde{\sigma}^2 = \frac{(Y_1^* - X_1^*\tilde{\beta})' V_{11}^{*-1} (Y_1^* - X_1^*\tilde{\beta})}{df_1} \tag{B.7}$$

and df_1 is the number of degrees of freedom (the number of observations minus the number of elements of β).

The best linear unbiased forecast of Y_2 (given V^* and X_2), say $\tilde{Y}_2$, is

$$\tilde{Y}_2 = X_2\tilde{\beta} + V_{21}^* V_{11}^{*-1}(Y_1^* - X_1^*\tilde{\beta}) \tag{B.8}$$

and the estimated covariance matrix of forecast errors, $\sum_{\tilde{Y}_2\tilde{Y}_2}$, is

$$\begin{aligned}\sum\nolimits_{\tilde{Y}_2\tilde{Y}_2} &= (X_2 - V_{21}^* V_{11}^{*-1}X_1^*) \sum\nolimits_{\tilde{\beta}\tilde{\beta}}(X_2 - V_{21}^* V_{11}^{*-1}X_1^*)' \\ &\quad - \tilde{\sigma}^2 V_{21}^* V_{11}^{*-1} V_{21}^{*\prime} + \tilde{\sigma}^2 V_{22}^*\end{aligned} \tag{B.9}$$

Replacing the data from the aggregate state with data at the national level is equivalent to premultiplying Y_1^* and X_1^* by a nonsingular aggregation matrix A:

$$Y_1 = AY_1^*$$

$$X_1 = AX_1^*$$

Note that the A matrix is defined so that premultiplication by A reproduces the data from the 15 individual states and also takes weighted averages of the data from the 15 states and the 16th aggregate state to yield the national-level data. Thus Y_1 and X_1 contain data for the 15 individual states and for the national aggregate.

From Eq. (B.1), the transformed data obey the relationship

$$Y_1 = X_1\beta + U_1 \tag{B.10}$$

where $U_1 = AU_1^*$. From Eq. (B.4), the relationships between elements of U_1 and U_2 are given by

$$E\begin{pmatrix} U_1 \\ U_2 \end{pmatrix}(U_1' \ U_2) = \sigma^2 \begin{pmatrix} V_{11} & V_{21}' \\ V_{21} & V_{22} \end{pmatrix} = \sigma^2 V$$

where $V_{11} = AV_{11}^*A'$, $V_{21} = V_{21}^*A'$, and $V_{22} = V_{22}^*$.

The GLS estimator of β in the transformed data, say $\bar{\beta}$, is

$$\begin{aligned}\bar{\beta} &= (X_1'V_{11}^{-1}X_1)^{-1}X_1'V_{11}^{-1}Y_1 \\ &= (X_1^{*\prime}A'A'^{-1}V_{11}^{*-1}A^{-1}AX_1^*)^{-1}X_1^{*}A'A'^{-1}V_{11}^{*}A^{-1}AY_1^* \\ &= \tilde{\beta} \qquad \text{(from Eq. (B.5))}\end{aligned} \tag{B.11}$$

Hence, replacing data from the aggregate state with national aggregate data leaves the estimator of β unchanged. The estimated covariance matrix of $\bar{\beta}$, say $\sum_{\bar{\beta}\bar{\beta}}$, is also identical to that of $\tilde{\beta}$:

$$
\begin{aligned}
\textstyle\sum_{\bar{\beta}\bar{\beta}} &= \bar{\sigma}^2(X_1' V_{11}^{-1} X_1)^{-1} \\
&= \bar{\sigma}^2(X_1^{*\prime} A' A'^{-1} V_{11}^{*-1} A^{-1} A X_1^{*})^{-1} \qquad \text{(B.12)} \\
&= \bar{\sigma}^2(X_1^{*\prime} V_{11}^{*-1} X_1^{*})^{-1}
\end{aligned}
$$

But
$$
\begin{aligned}
\bar{\sigma}^2 &= \frac{(Y_1 - X_1\bar{\beta})' V_{11}^{-1}(Y_1 - X_1\bar{\beta})}{df_2} \\
&= \frac{(AY_1^{*} - AX_1^{*}\tilde{\beta})' A'^{-1} V_{11}^{*-1} A^{-1}(AY_1^{*} - AX_1^{*}\tilde{\beta})}{df_1} \\
&= \tilde{\sigma}^2
\end{aligned}
$$

Therefore, $\quad \sum_{\bar{\beta}\bar{\beta}} = \sum_{\tilde{\beta}\tilde{\beta}}$

Using the transformed data, the best linear unbiased forecast of Y_2 (given V and X_2), say $\bar{Y}_2$, is

$$
\begin{aligned}
\bar{Y}_2 &= X_2\bar{\beta} + V_{21} V_{11}^{-1}(Y_1 - X_1\bar{\beta}) \\
&= X_2\tilde{\beta} + V_{21}^{*} A' A'^{-1} V_{11}^{*-1} A^{-1}(AY_1^{*} - AX_1^{*}\tilde{\beta}) \qquad \text{(B.13)} \\
&= \tilde{Y}_2
\end{aligned}
$$

The estimated covariance matrix of forecast errors is

$$
\begin{aligned}
\textstyle\sum_{\bar{Y}_2\bar{Y}_2} &= (X_2 - V_{21} V_{11}^{-1} X_1) \textstyle\sum_{\bar{\beta}\bar{\beta}} (X_2 - V_{21} V_{11}^{-1} X_1)' \\
&\quad + \bar{\sigma}^2(V_{22} - V_{21} V_{11}^{-1} V_{21}') \\
&= (X_2 - V_{21}^{*} A' A'^{-1} V_{11}^{*-1} A^{-1} A X_1^{*}) \textstyle\sum_{\tilde{\beta}\tilde{\beta}} (X_2 \qquad \text{(B.14)} \\
&\quad - V_{21}^{*} A' A'^{-1} V_{11}^{*-1} A^{-1} A X_1^{*})' \\
&\quad + \tilde{\sigma}^2(V_{22}^{*} - V_{21}^{*} A' A'^{-1} V_{11}^{*-1} A^{-1} A V_{21}^{*\prime}) \\
&= \textstyle\sum_{\tilde{Y}_2\tilde{Y}_2}
\end{aligned}
$$

Hence, forecasts and the estimated covariance matrix of forecast errors are unchanged.

THE GLS ESTIMATION PROCEDURE

The GLS procedure is examined next in some detail. To begin, a specific though arbitrary ordering is imposed on the data. First, let the s (state) index be defined to range over $s = 1, ..., S_1, ..., S_2$, where the first S_1 states are those for which data will be entered individually in the GLS procedure. (For the purposes of this report, define $S_2 = 51$ and $S_1 = 15$.) Define the b (Service) index to range over $b = 1, ..., B$ ($B = 4$ in this application). Let the t (time) index range over $t = 1, ..., T_1$, where T_1 is the number of time-series observations for a particular state and Service ($T_1 = 78$ in this report). Now order the data for the S_1 states and the national aggregate by Service within time period within state. That is, the data are first sorted by the state index with the national aggregate coming last; the data for each of the S_1 states (and the national aggregate) are then sorted by time period; and, finally, the data are ordered by Service within each time period and state (including the national aggregate). In Eq. (B.10), the vector U_1 with representative element u_{bst} is then of the form:

$$U_1 = (u_{111}\ u_{211} ... u_{B11}\ u_{112} ... u_{B12} ... u_{11T_1} ... u_{B1T_1}\ u_{121} ... u_{B2T_1}$$
$$... u_{1S_1 1} ... u_{BS_1 T_1}\ u_{1n1} ... u_{BnT_1})'$$

The same ordering of the data is, of course, used in Y_1 and X_1 of Eq. (B.10).

To write the model in quasi-differenced form, first define the matrix D as

$$D = I_{S_1+1} \otimes \left[\left(\left(I_{T_1-1} \otimes (-P)\right) | 0\right) + \left(0 | I_{B(T_1-1)}\right)\right]$$

where $P = \text{diag}\ \{\rho_1, ..., \rho_B\}$. The zero matrices in the above expression are of order $B(T_1 - 1) \times B$, and I_ℓ denotes an identity matrix of order ℓ. The quasi-differenced form of Eq. (B.10) is then

$$DY_1 = DX_1\beta + DU_1 \tag{B.15}$$

As stated in the text, the quasi-differenced disturbances for the 15 individual states are of the form

$$u_{bst} - \rho_b u_{bs\,t-1} = \varphi_{bst}$$

For the national aggregates, quasi-differenced disturbances are

$$u_{bnt} - \rho_b u_{bn\,t-1} = \sum_{s=1}^{S_2} (r_{st} u_{bst} - \rho_b r_{s\,t-1} u_{bs\,t-1})$$

Assuming that r_{st} remains unchanged over time for each individual state, as is approximately true over the observation period used here, then

$$\begin{aligned} u_{bnt} - \rho_b u_{bn\,t-1} &= \sum_{s=1}^{S_2} r_s\ (u_{bst} - \rho_b u_{bs\,t-1}) \\ &= \sum_{s=1}^{S_2} r_s \varphi_{bst} \\ &= \varphi_{bnt} \end{aligned}$$

where r_s is the unchanging value of r_{st} for any t. Thus, under the assumption that the r_{st} remain constant over time, the national-level disturbances also follow an AR(1) process, and hence quasi-differencing the national aggregates removes serial correlation here as well.

Although quasi-differencing removes all intertemporal correlations, contemporaneous correlations remain. To compute the contemporaneous correlations in the quasi-differenced data, first recall from Sec. II of the text that φ_{bst} for an individual state is the sum of two components:

$$\varphi_{bst} = \lambda_{bt} + \epsilon_{bst}$$

where $E(\lambda_{bt}) = E(\epsilon_{bst}) = 0$

$$E(\lambda_{bt}\lambda_{b't'}) = \begin{cases} \omega_{bb'} & \text{if } t = t' \\ 0 & \text{otherwise} \end{cases}$$

$$E(\epsilon_{bst}\epsilon_{b's't'}) = \begin{cases} \gamma_{bb'} & \text{if } t = t' \text{ and } s = s' \\ 0 & \text{otherwise} \end{cases}$$

$$E(\lambda_{bt}\epsilon_{b'st'}) = 0 \text{ for all } b, s, t, b', t'$$

Covariances between the φ_{bst} for individual states are thus given by

$$E(\varphi_{bst}\varphi_{b's't'}) = \begin{cases} \omega_{bb'} + \gamma_{bb'} & \text{if } t = t' \text{ and } s = s' \\ \gamma_{bb'} & \text{if } t = t' \text{ and } s \neq s' \\ 0 & \text{if } t \neq t' \end{cases}$$

The remaining covariances are

$$E(\varphi_{bst}\varphi_{b'nt'}) = \begin{cases} \omega_{bb'} + r_s\gamma_{bb'} & \text{if } t = t' \\ \\ 0 & \text{otherwise} \end{cases}$$

$$E(\varphi_{bnt}\varphi_{b'nt'}) = \begin{cases} \omega_{bb'} + \gamma_{bb'} \sum_{s=1}^{S_2} r_s^2 & \text{if } t = t' \\ 0 & \text{otherwise} \end{cases}$$

The complete covariance matrix of the disturbance vector DU_1 may therefore be written as

$$\begin{aligned} E(DU_1U_1'D') &= (J_{S_1+1} \otimes I_{T_1-1} \otimes \Omega) + (C \otimes I_{T_1-1} \otimes \Gamma) \\ &= Q \end{aligned}$$

where $C = \begin{pmatrix} I_{S_1} & r \\ \\ r' & \sum_{s=1}^{S_2} r_s^2 \end{pmatrix}$

$r = (r_1, \ldots, r_{S_1})'$

Ω = a $B \times B$ matrix with typical element $\omega_{bb'}$

Γ = a $B \times B$ matrix with typical element $\gamma_{bb'}$

and J_ℓ = an $\ell \times \ell$ matrix of ones.

The GLS estimator of β in the quasi-differenced data is

$$\hat{\beta} = (X_1'D'Q^{-1}DX_1)^{-1} X_1'D'Q^{-1}DY_1 \qquad \text{(B.16)}$$

and the covariance matrix of $\hat{\beta}$ is

$$\sum_{\hat{\beta}\hat{\beta}} = (X_1'D'Q^{-1}DX_1)^{-1} \tag{B.17}$$

The matrices Q and D appearing in Eqs. (B.16) and (B.17) contain elements that are unknown *a priori* and must therefore be estimated. The values of r_s in the matrix Q were estimated by computing the average value of r_{st} for each state s over the interval July 1972 through September 1981. The remaining elements of D and Q are the parameters ρ_b, $\omega_{bb'}$, and $\gamma_{bb'}$. The method of estimating these parameters is described in Sec. III of the text, but will now be repeated for completeness.

Values of ρ_b were obtained in two steps. First, using data from the 15 individual states, an OLS regression of the enlistment rate on the explanatory variables was run for each separate Service. That is, Y_1 *without* the national aggregate data was regressed on X_1 *without* the national aggregate data. The regression residuals for each Service were then regressed on the first lagged value of the residuals. The resulting coefficient estimate from the latter regression for each Service is an estimate of ρ_b.

The estimated values of ρ_b were used to quasi-difference the data for the 15 individual states, and these quasi-differenced data were used in another round of OLS for each Service. That is, $\hat{D}Y_1$ *without* the national aggregate data was regressed on $\hat{D}X_1$ *without* the national aggregate data, where $\hat{D}$ is the estimated D obtained by replacing ρ_b with their estimated values. Sample moments of the residuals from this regression were used to estimate the contemporaneous covariances $\omega_{bb'}$ and $\gamma_{bb'}$ as follows.[3] Letting e_{bst} denote the residual for Service b in state s at time t, $\omega_{bb'}$ was estimated as the average value of $e_{bst}e_{b's't}$ computed over all pairs of non-identical states ($s \neq s'$) and all months.[4] That is,

$$\hat{\omega}_{bb'} = \left(\sum_{s}\sum_{s'\neq s}\sum_{t} e_{bst}e_{b's't}\right)\Big/ S_1(S_1 - 1)(T_1 - 1)$$

where S_1 is the number of individual states included (15) and $T_1 - 1$ is the number of observations per state in the quasi-differenced data (77). Next $\omega_{bb'} + \gamma_{bb'}$ was estimated as the average value of $e_{bst}e_{b'st}$ computed over states s and months t. That is,

[3]My procedure for estimating the elements of Q differs from Parks' in that I make no degrees of freedom corrections. However, the justification for this whole estimation scheme is asymptotic, and degrees of freedom corrections do not matter asymptotically.

[4]Because the residual is from quasi-differenced data, the residual at time t is based upon raw data from times t and $t + 1$.

$$\widehat{\omega_{bb'} + \gamma_{bb'}} = \left(\sum_s \sum_t e_{bst} e_{b'st}\right) \Big/ S_1(T_1 - 1)$$

The estimated value of $\gamma_{bb'}$ was then obtained as

$$\hat{\gamma}_{bb'} = \widehat{\omega_{bb'} + \gamma_{bb'}} - \hat{\omega}_{bb'}$$

The estimates of $\omega_{bb'}$ and $\gamma_{bb'}$ were then used to form an estimated value of Q, say $\hat{Q}$. The GLS coefficient estimates reported in the text have been computed as in Eq. (B.16), with D and Q replaced by their estimated values, $\hat{D}$ and $\hat{Q}$.

In principle, the asymptotic standard errors of $\hat{\beta}$ may be computed by replacing D and Q in Eq. (B.17) with their estimated values. I have instead reported the somewhat more conservative (larger) standard errors obtained by multiplying each element on the right-hand side of Eq. (B.17) by $\hat{\sigma}^2$, computed as

$$\hat{\sigma}^2 = (\hat{D}Y_1 - \hat{D}X_1\hat{\beta})'\hat{Q}^{-1}(\hat{D}Y_1 - \hat{D}X_1\hat{\beta}) \Big/ ((T_1 - 1)(S_1 + 1) - k)$$

where k is the number of elements of β.[5]

THE COMPUTATION OF FORECASTS AND THEIR STANDARD ERRORS

Computation of forecasts and their standard errors proceeds under the assumption that the covariance matrix of the disturbances and future values of the explanatory variables are known. Forecasts of the monthly national enlistment rates are computed as

$$\hat{Y}_2 = X_2\hat{\beta} + V_{21}V_{11}^{-1}\,(Y_1 - X_1\hat{\beta}) \qquad \text{(B.18)}$$

These forecasts would be best (minimum mean squared prediction error) linear unbiased if $\hat{\beta}$ in Eq. (B.18) were computed over all of the time-series data. As noted above, however, $\hat{\beta}$ is instead computed from quasi-differenced data, which have one less element in each of the component time series. As a consequence, the best linear unbiased prediction of Y_2 using this $\hat{\beta}$ would differ from Eq. (B.18) in the final term. This difference is negligible, however, and in addition the form given in Eq. (B.18) is slightly easier to compute.

The computation of $V_{21}V_{11}^{-1}$ uses data ordered as described in the preceding subsection, where the same ordering is now imposed on the

[5]The Parks procedure does not make such an adjustment.

forecast period "observations" for the national aggregates. The elements of V_{21} and V_{11} are obtained from Eq. (4) in the text and from the following relationships derived from the definition of the national-level disturbance u_{bnt}:

$$E(u_{bst}u_{b'nt'}) = (\omega_{bb'} + r_s\gamma_{bb'})g\Big/(1 - \rho_b\rho_{b'})$$

where $$g = \begin{cases} \rho_b^{t-t'} & \text{if } t \geq t' \\ \rho_{b'}^{t'-t} & \text{if } t' \geq t \end{cases}$$

$$E(u_{bnt}u_{b'nt'}) = \left(\omega_{bb'} + \gamma_{bb'}\sum_{s=1}^{S_2} r_s^2\right)\rho_b^{t-t'}\Big/(1 - \rho_b\rho_{b'})$$

where $t \geq t'$.

The matrix V_{11} is thus of the form

$$V_{11} = (J_{S_1+1} \otimes W_1) + (C \otimes W_2)$$

where $$W_1 = \begin{pmatrix} L_1 & L_1 P & L_1P^2 & \cdots & L_1P^{T_1-1} \\ P L_1 & L_1 & L_1P & \cdots & L_1P^{T_1-2} \\ P^2L_1 & PL_1 & L_1 & \cdots & \cdot \\ \cdot & \cdot & & & \cdot \\ \cdot & \cdot & & & \cdot \\ \cdot & \cdot & & & \\ P^{T_1-1}L_1 & P^{T_1-2}L_1 & & \cdots & L_1 \end{pmatrix}$$

$$W_2 = \begin{pmatrix} L_2 & L_2 P & L_2P^2 & \cdots & L_2P^{T_1-1} \\ P L_2 & L_2 & L_2P & \cdots & L_2P^{T_1-2} \\ P^2L_2 & PL_2 & L_2 & \cdots & \cdot \\ \cdot & \cdot & & & \cdot \\ \cdot & \cdot & & & \cdot \\ \cdot & \cdot & & & \\ P^{T_1-1}L_2 & P^{T_1-2}L_2 & & \cdots & L_2 \end{pmatrix}$$

and L_1 = a $B \times B$ matrix with typical element $\omega_{bb'}/(1 - \rho_b\rho_{b'})$

L_2 = a $B \times B$ matrix with typical element $\gamma_{bb'}/(1 - \rho_b\rho_{b'})$

The matrix V_{21} may be written as

$$V_{21} = (\iota'_{S_1+1} \otimes W_3) + \left(\left(r' \Big| \sum_{s=1}^{S_2} r_s^2\right) \otimes W_4\right)$$

where

$$W_3 = \begin{pmatrix} P^{T_1}L_1 & P^{T_1-1}L_1 & \cdots & P\,L_1 \\ P^{T_1+1}L_1 & P^{T_1}L_1 & \cdots & P^2L_1 \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ P^{T_2-1}L_1 & \cdots & & P^{T_2-T_1}L_1 \end{pmatrix}$$

$$W_4 = \begin{pmatrix} P^{T_1}L_2 & P^{T_1-1}L_2 & \cdots & P\,L_2 \\ P^{T_1+1}L_2 & P^{T_1}L_2 & \cdots & P^2L_2 \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ P^{T_2-1}L_2 & \cdots & & P^{T_2-T_1}L_2 \end{pmatrix}$$

ι'_ℓ = an $\ell \times 1$ row vector of ones, and T_2 is the time (t) of the final month in the forecast interval.

Notice that V_{21} may be viewed as composed of $T_2 - T_1$ groups of B row blocks, and the ℓth such group is equal to the final B rows of V_{11} premultiplied by P^ℓ. That is, V_{21} may be written as

$$V_{21} = \left(\mathrm{diag}\{P^1, \ldots, P^{T_2-T_1}\}\right)\left(\iota_{T_2-T_1} \otimes V_{11.}\right) \qquad \text{(B.19)}$$

where $V_{11.}$ is the last B rows of V_{11}. Because $V_{11}V_{11}^{-1} = I$, it follows from Eq. (B.19) that

$$V_{21}V_{11}^{-1} = \left(\mathrm{diag}\{P^1, \ldots, P^{T_2-T_1}\}\right)\left(\iota_{T_2-T_1} \otimes (0 \,|\, I_B)\right) \qquad \text{(B.20)}$$

where the zero matrix in the above expression is of order $B \times B((S_1 + 1)T_1 - 1)$. When the value of $V_{21}V_{11}^{-1}$ from Eq. (B.20) is inserted into Eq. (B.18), and the result is written out in detail, the predicted enlistment rate $\hat{y}_{bnt}$ for Service b at the national level at time t, $T_1 < t \leq T_2$, is

$$\hat{y}_{bnt} = \sum_j x_{bntj}\hat{\beta}_{bj} + \rho_b^{t-T_1}\hat{u}_{bnT_1} \tag{B.21}$$

In application, ρ_b are replaced by their estimated values, yielding Eq. (6) in the text.[6]

Predicted enlistment levels for an out-of-sample fiscal year f, $\hat{y}_{bnf}$, are formed by multiplying the predicted monthly enlistment rates given in Eq. (B.21) by the national youth population in each month (pop_t), and summing across months of the fiscal year:

$$\hat{y}_{bnf} = \sum_t \hat{y}_{bnt}pop_t \tag{B.22}$$

where the summation ranges over all months in fiscal year f. To express this computation in matrix form, define h_f' to be a row vector whose elements are the pop_t in each month of fiscal year f. The vector of predicted enlistments by Service for all fiscal years f, $f = 1, ..., F$, is $H\hat{Y}_2$,

where $H = \text{diag}\{h_1' \otimes I_B, h_2' \otimes I_B, ..., h_F' \otimes I_B\}$

The DoD totals for each fiscal year are formed in straightforward fashion by summing the Service-specific totals for that fiscal year.

Standard errors for predictions are most easily constructed by first considering $\sum_{\hat{Y}_2\hat{Y}_2}$, the variance in the prediction error for monthly enlistment rates:

$$\begin{aligned}\sum\nolimits_{\hat{Y}_2\hat{Y}_2} = \hat{\sigma}^2\Big[&(X_2 - V_{21}V_{11}^{-1}X_1)\sum\nolimits_{\hat{\beta}\hat{\beta}}(X_2 - V_{21}V_{11}^{-1}X_1)' \\ &+ (V_{22} - V_{21}V_{11}^{-1}V_{21}')\Big]\end{aligned} \tag{B.23}$$

[6]It was noted above that these forecasts differ very slightly from best linear unbiased forecasts based upon quasi-differenced data. The latter forecasts are the same as in Eq. (B.21) with the addition of the term $-\rho_b^t\hat{u}_{bn1}$.

where

$$V_{22} = \begin{pmatrix} L_3 & L_3P & L_3P^2 & \cdots & L_3P^{T_2-T_1-1} \\ PL_3 & L_3 & L_3P & \cdots & \cdot \\ P^2L_3 & PL_3 & L_3 & \cdots & \cdot \\ \cdot & & & & \cdot \\ \cdot & & & & \\ \cdot & & & & \\ P^{T_2-T_1-1}L_3 & \cdots & & & L_3 \end{pmatrix}$$

and $L_3 = L_1 + \left(\sum_{s=1}^{S_2} r_s^2\right)L_2$.

Using the results given in Eqs. (B.19) and (B.20) yields

$$V_{21}V_{11}^{-1}V_{21}' = \left(\mathrm{diag}\{P, P^2, ..., P^{T_2-T_1}\}\right)\left(J_{T_2-T_1} \otimes L_3\right)$$

$$\left(\mathrm{diag}\{P, P^2, ..., P^{T_2-T_1}\}\right)$$

Finally, from Eq. (B.20), the expression $V_{21}V_{11}^{-1}X_1$ in Eq. (B.23) may be written as

$$V_{21}V_{11}^{-1}X_1 = \left(\mathrm{diag}\{P^1, P^2, ..., P^{T_2-T_1}\}\right)\left(\iota_{T_2-T_1} \otimes X_{nT_1}\right)$$

where X_{nT_1} is a $B \times k$ matrix of values of national aggregate explanatory variables at time T_1. Hence the term $(X_2 - V_{21}V_{11}^{-1}X_1)$ in Eq. (B.23) takes national aggregate variables at each t (where $t > T_1$) and deducts $\rho_b^{t-T_1}$ times the corresponding national aggregate variables at time T_1.

Because the predicted fiscal year enlistment levels are obtained as $H\hat{Y}_2$, i.e., as population-weighted sums of the predicted monthly enlistment rates, the covariance matrix of prediction errors on the fiscal year enlistment levels is

$$H \sum\nolimits_{\hat{Y}_2\hat{Y}_2} H'$$

Appendix C

ESTIMATION AND FORECASTING RESULTS FOR AFQT CATEGORY IIIB

This appendix contains the estimation and forecasting results for NPS male HSDGs in AFQT category IIIB. The analysis parallels the general model presented in the text for the I-IIIA group.

The estimates of the autoregressive parameters ρ_b for the IIIB group are 0.494 for the Army, 0.352 for the Navy, 0.302 for the Marine Corps, and 0.336 for the Air Force. Tables C.1 through C.4 present estimates of correlations between disturbances at a point in time, as is done for the I-IIIA group in Tables 2 through 5 in the text. Table C.5 gives the parameter estimates of interest. Tables C.6 through C.9 give the forecasts for the four scenarios discussed in the text, and Table C.10 compares actual values with predicted values over the observation interval.

The parameter estimates in Table C.5, particularly pay and recruiter effects, may look strange if interpreted as estimates of pure supply effects. The problem here may be that entry of the IIIB group has been constrained by the Services over some portion of the observation interval. If so, then these coefficient estimates do not represent pure supply responses but are instead a mixture of supply responses and military demand effects.

Table C.1

ESTIMATED CORRELATIONS OF NATIONAL COMPONENTS (λ_{bt}) AT A POINT IN TIME (AFQT Category IIIB)

Service	Army	Navy	Marine Corps	Air Force
Army	1	0.782	0.748	0.347
Navy		1	0.523	0.178
Marine Corps			1	0.551
Air Force				1

Table C.2

ESTIMATED CORRELATIONS OF STATE-SPECIFIC COMPONENTS (ϵ_{bst}) WITHIN STATES AT A POINT IN TIME (AFQT Category IIIB)

Service	Army	Navy	Marine Corps	Air Force
Army	1	−0.014	0.040	0.004
Navy		1	0.046	0.134
Marine Corps			1	0.129
Air Force				1

Table C.3

ESTIMATED CORRELATIONS OF NEW NOISE (φ_{bst}) ACROSS STATES AT A POINT IN TIME (AFQT Category IIIB)

Service	Army	Navy	Marine Corps	Air Force
Army	0.131	0.096	0.097	0.066
Navy		0.114	0.064	0.032
Marine Corps			0.129	0.104
Air Force				0.274

Table C.4

ESTIMATED CORRELATIONS OF NEW NOISE (φ_{bst}) WITHIN STATES AT A POINT IN TIME (AFQT Category IIIB)

Service	Army	Navy	Marine Corps	Air Force
Army	1	0.083	0.132	0.069
Navy		1	0.104	0.139
Marine Corps			1	0.206
Air Force				1

Table C.5

GENERALIZED LEAST SQUARES ESTIMATES: HIGH SCHOOL DIPLOMA GRADUATE MALES IN AFQT CATEGORY IIIB

Variable	Army	Navy	Marine Corps	Air Force
GIBILL				
Coefficient estimate (×1000)[a]	0.06449	0.02274	0.00247	−0.01383
Asymptotic standard error (×1000)	0.01218	0.00621	0.00404	0.00896
Asymptotic normal statistic	5.3	3.66	0.61	−1.54
Effect on yearly enlistments of replacing VEAP with GI Bill	7911	2790	303	−1696
% effect on enlistments of replacing VEAP with GI Bill	64.7	25.6	4.8	−11.9
LREC				
Coefficient estimate (×1000)[a]	−0.0366	0.00697	0.00803	0.12576
Asymptotic standard error (×1000)	0.07085	0.02464	0.04054	0.03006
Asymptotic normal statistic	−0.52	0.28	0.20	4.18
Effect on yearly enlistments of 0.01 increase	−45	9	10	154
% effect on enlistments of 0.01 (1%) increase	−0.368	0.083	0.157	1.08
LWPAY				
Coefficient estimate (×1000)[a]	0.16672	−0.00704	0.01380	0.03744
Asymptotic standard error (×1000)	0.06413	0.03627	0.02406	0.03917
Asymptotic normal statistic	2.60	−0.19	0.57	0.96
Effect on yearly enlistments of 0.01 increase	204	−9	17	46
% effect on enlistments of 0.01 (1%) increase	1.67	−0.083	0.267	0.323
CYCLE				
Coefficient estimate (×1000)[a]	−0.10464	−0.4102	−0.15731	−0.14229
Asymptotic standard error (×1000)	0.10679	0.05154	0.03415	0.05668
Asymptotic normal statistic	−0.98	−7.96	−4.61	−2.51
Effect on yearly enlistments of 0.01 increase	−128	−503	−193	−175
Peak-to-trough change in enlistments as % of normal enlistments	15.3	67.4	44.1	17.9

[a]Reported coefficient estimate is 1000 times the effect of a unit change in the explanatory variable on the monthly enlistment rate. See text for variable definitions.

Table C.6

FORECASTS OF ENLISTMENTS OF HIGH SCHOOL DIPLOMA GRADUATE MALES IN AFQT CATEGORY IIIB BY FISCAL YEAR[a]
(DRI Unemployment Rate Scenario)

Fiscal Year	Army	Navy	Marine Corps	Air Force	DoD Total[b]
1982	13660	15149	8043	15607	52459
	(2155)	(823)	(549)	(1110)	(3302)
1983	13011	13988	7560	15322	49881
	(2207)	(746)	(504)	(1055)	(3314)
1984	12189	12403	6907	14902	46401
	(2328)	(677)	(511)	(1014)	(3419)
1985	11585	11693	6587	14776	44640
	(2479)	(673)	(583)	(1023)	(3622)
1986	11065	11124	6325	14674	43189
	(2617)	(683)	(667)	(1043)	(3826)
1987	10752	10780	6166	14608	42306
	(2703)	(695)	(724)	(1058)	(3957)
1988	10671	10607	6094	14557	41928
	(2724)	(696)	(735)	(1061)	(3983)
1989	10550	10410	6011	14503	41474
	(2756)	(701)	(754)	(1068)	(4028)
1990	10335	10207	5914	14465	40921
	(2816)	(713)	(797)	(1081)	(4125)

[a]Standard error of forecast is given in parentheses.
[b]DoD total may not equal sum across Services because of rounding.

Table C.7

FORECASTS OF ENLISTMENTS OF HIGH SCHOOL DIPLOMA GRADUATE MALES IN AFQT CATEGORY IIIB BY FISCAL YEAR[a]
(Recessionary Scenario)

Fiscal Year	Army	Navy	Marine Corps	Air Force	DoD Total[b]
1982	13660	15149	8043	15607	52459
	(2155)	(823)	(549)	(1210)	(3302)
1983	13626	16399	8485	16158	54669
	(2359)	(934)	(617)	(1209)	(3620)
1984	13091	15937	8262	16128	53418
	(2446)	(909)	(622)	(1194)	(3731)
1985	12546	15464	8033	16084	52127
	(2546)	(892)	(658)	(1187)	(3876)
1986	12064	15040	7827	16032	50963
	(2642)	(884)	(712)	(1188)	(4028)
1987	11774	14784	7702	15996	50256
	(2702)	(882)	(752)	(1192)	(4127)
1988	11726	14743	7681	15992	50141
	(2713)	(882)	(759)	(1193)	(4145)
1989	11634	14660	7641	15977	49912
	(2732)	(882)	(773)	(1194)	(4177)
1990	11423	14472	7550	15944	49389
	(2776)	(883)	(805)	(1199)	(4253)

[a]Standard error of forecast is given in parentheses.

[b]DoD total may not equal sum across Services because of rounding.

Table C.8

FORECASTS OF ENLISTMENTS OF HIGH SCHOOL DIPLOMA GRADUATE MALES IN AFQT CATEGORY IIIB BY FISCAL YEAR[a]
(On-Trend Employment-Growth Scenario)

Fiscal Year	Army	Navy	Marine Corps	Air Force	DoD Total[b]
1982	12634	11128	6500	14212	44474
	(2151)	(656)	(442)	(992)	(3126)
1983	12218	10878	6368	14243	43707
	(2266)	(649)	(458)	(994)	(3259)
1984	11724	10580	6208	14270	42782
	(2407)	(651)	(513)	(1005)	(3447)
1985	11223	10274	6043	14284	41824
	(2553)	(664)	(597)	(1025)	(3663)
1986	10779	10001	5894	14284	40958
	(2683)	(683)	(683)	(1050)	(3868)
1987	10511	9836	5804	14280	40431
	(2761)	(698)	(739)	(1067)	(3997)
1988	10467	9810	5789	14281	40347
	(2775)	(700)	(748)	(1070)	(4019)
1989	10383	9756	5760	14276	40175
	(2799)	(705)	(766)	(1076)	(4060)
1990	10189	9634	5694	14266	39783
	(2855)	(718)	(808)	(1089)	(4154)

[a]Standard error of forecast is given in parentheses.

[b]DoD total may not equal sum across Services because of rounding.

Table C.9

FORECASTS OF ENLISTMENTS OF HIGH SCHOOL DIPLOMA GRADUATE MALES IN AFQT CATEGORY IIIB BY FISCAL YEAR[a]
(Expansionary Scenario)

Fiscal Year	Army	Navy	Marine Corps	Air Force	DoD Total[b]
1982	12161	9274	5790	13569	40794
	(2315)	(698)	(471)	(1037)	(3278)
1983	11756	9069	5674	13615	40115
	(2427)	(694)	(496)	(1042)	(3411)
1984	11276	8825	5535	13661	39297
	(2564)	(699)	(557)	(1055)	(3597)
1985	10789	8574	5391	13694	38447
	(2706)	(714)	(642)	(1076)	(3808)
1986	10357	8350	5261	13711	37679
	(2832)	(733)	(728)	(1101)	(4009)
1987	10098	8215	5182	13718	37212
	(2907)	(748)	(783)	(1118)	(4135)
1988	10055	8193	5169	13720	37137
	(2920)	(751)	(793)	(1121)	(4156)
1989	9973	8149	5144	13718	36984
	(2943)	(756)	(810)	(1126)	(4196)
1990	9785	8048	5086	13716	36635
	(2997)	(768)	(851)	(1140)	(4288)

[a]Standard error of forecast is given in parentheses.

[b]DoD total may not equal sum across Services because of rounding.

Table C.10

PREDICTED ENLISTMENTS OF HIGH SCHOOL DIPLOMA GRADUATE MALES IN AFQT CATEGORY IIIB OVER THE OBSERVATION INTERVAL BY FISCAL YEAR[a]

Fiscal Year	Army	Navy	Marine Corps	Air Force
1975[b]	27896	14213	8328	13259
	(27182)	(14703)	(8036)	(13326)
1976	24335	14703	7699	10661
	(23919)	(14904)	(7673)	(10866)
1977	18103	13891	6827	12828
	(17665)	(13777)	(6819)	(12614)
1978	13538	11031	6163	11586
	(14040)	(10488)	(6238)	(10723)
1979	12502	10526	6185	11548
	(11898)	(9922)	(5767)	(11346)
1980	12214	11680	6630	14364
	(12265)	(12332)	(6907)	(16346)
1981	6472	6242	3591	7953
(first six months)	(7168)	(6424)	(3822)	(7286)

[a]Actual enlistments are in parentheses below the predicted value. Unlike the predictions for the forecast interval given in the preceding tables, these predictions use only the deterministic portion of Eq. (1).

[b]For purposes of this table, fiscal year 1975 is defined to run from October 1974 through September 1975; fiscal year 1976 is defined to run from October 1975 through September 1976.

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